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Essays on Macroeconomic Analysis of Development

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ESSAYS ON MACROECONOMIC ANALYSIS OF DEVELOPMENT

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Nazmul Islam

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DEDICATION

For my mother, Khadeja Begum, my late father, Nurul Huda, my wife, my late grandparents, my brothers and sisters, my aunts and uncles, and my nephews and nieces. They are my source of inspiration. They have been motivating and supporting me to reach my career goals.

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ABSTRACT OF THE DISSERTATION

ESSAYS ON MACROECONOMIC ANALYSIS OF DEVELOPMENT

by

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This dissertation includes three essays on empirical studies of macroeconomic analysis of development. The first and second chapter focus on defining different categories of households based on the type of wealth they hold, deriving their demographic characteristics and how they react to transitory income shocks. The economics literature splits households into poor hand-to-mouth (P-HtM), wealthy hand-to-mouth (W-HtM), and not hand-to-mouth (N-HtM). This breakdown is important to accurately capture how different categories of households react to income shocks.

In Chapter 1, I argue that this classification is missing important features related to the behavior of indebted households. Thus, novel in the literature, I define a new category of households: the indebted poor hand-to-mouth (IP-HtM), those that hold no net liquid assets (cash, checking, savings accounts etc.) and are indebted in illiquid wealth (negative net value of illiquid wealth defined as a negative net mortgage value that is not offset by positive illiquid assets such as private retirement accounts). I identify the share of such households in the United States, their demographic characteristics, their portfolio composition, and the persistence of their status over their life cycle. In the literature, they assimilate into the P-HtM households that hold neither net liquid nor net

illiquid assets. However, I show that the age profile of IP-HtM households by demographic characteristics demonstrates almost the same pattern as W-HtM households that do not hold liquid assets but own sizable amounts of illiquid wealth.

In the second chapter, I perform a detailed analysis of how various items of consumption such as food, nonfood, durable, nondurable, social sector, healthcare, utilities and education expenditure respond to transitory income shocks. The IP-HtM exhibits the highest marginal propensity to consume among all categories of households, for most consumption items. This implies that the stimulatory government's policies are the most effective for the IP-HtMs. This research can help governments design and execute their fiscal policies targeting the highest stimulatory effect during recessions.

In the third chapter, I use a 2013 survey of rickshaw pullers in Dhaka, Bangladesh to identify the determinants of their households' healthcare expenditure using a flexible Box-Cox model regression method. The results suggest that income, distance of residence from healthcare center/hospital, age of household head, and duration of illness episode are the main determinants of healthcare utilization. The income elasticity of about 0.55 signals the tendency for healthcare to behave like a normal and necessary good. Since healthcare is a necessity in the "basic needs" theory of economic development, the way healthcare expenditure in a resource-constrained community responds to changes in income level and other factors is particularly relevant to development policy. Working-class populations in developing countries have unmet healthcare needs, and effective policies and programs are needed to ensure that healthcare services are received in a timely manner.

TABLE OF CONTENTS

CHAPTER PAGE

INTRODUCTION ... 1

1. THE INDEBTED HAND-TO-MOUTH ... 6
1.1 Introduction ... 6
1.2 Literature Review ... 8
1.3 Data and Methodology ... 10
1.4 The Share of Indebted Hand-to-Mouth Households ... 14
1.5 Demographics and Portfolio Composition of Indebted Hand-to-Mouth Households ... 16
1.6 The Share of Indebted Hand-to-Mouth Households Based on Race and Regions ... 18
1.7 Status Persistence of Indebted Hand-to-Mouth Households in PSID Data ... 19
1.8 Conclusion ... 20
TABLES ... 22
FIGURES ... 27
APPENDIX ... 35

2. CONSUMPTION RESPONSE OF THE INDEBTED HAND-TO-MOUTH HOUSEHOLDS TO TRANSITORY INCOME SHOCKS ... 37
2.1 Introduction ... 37
2.2 Literature Review ... 39
2.3 Data and Methodology ... 43
2.3.1 Data Source, Sample Selection and Definitions ... 43
2.3.2 Methodology ... 44
2.4 Results and Robustness ... 45
2.5 Conclusion ... 49
TABLES ... 51

3. DETERMINANTS OF HEALTHCARE EXPENDITURE OF A RESOURCE-CONSTRAINED COMMUNITY: EVIDENCE FROM RICKSHAW PULLERS ... 60
3.1 Introduction ... 60
3.2 Literature Review ... 64
3.3 Data and Methodology ... 68
3.3.1 Data ... 68
3.3.2 Empirical Regression Model Specification ... 69
3.4 Descriptive Statistics ... 77
3.5 Results ... 78
3.6 Summary, Conclusions, and Implications ... 82
TABLES ... 86
APPENDIX ... 92

REFERENCES 96

VITA 107

LIST OF TABLES

TABLE PAGE

Table 1. 1 Summary Information on the Survey Data Used 22

Table 1. 2 Definitions of Income, Liquid assets, Liquid Debts, and
Net Illiquid wealth (SCF) 22

Table 1. 3 Household Income, Liquid and Illiquid Wealth Holdings, and Portfolio
Composition 23

Table 1. 4 Robustness Results for Fraction HtM in Each HtM Category 24

Table 1. 5 Definitions of Consumption, Income, Liquid Assets, Liquid Debts and
Net Illiquid Wealth (PSID) 25

Table 1. 6 Fraction of HtM Households, PSID pooled 1999-2015 Waves,
United States 25

Table 1. 7 Percentage of IP-HtM, NIP-HtM, and W-HtM Households
Based on Races 25

Table 1. 8 Percentage of IP-HtM, NIP-HtM, and W-HtM Households
Based on Regions 26

Table 1. 9 Probability of Forward Transient state of HtM Households 26

Table 1. 10 Probability of Backward Transient state of HtM Households 26

Table A1. 1 Portfolio Characteristics by HtM Status. 35

Table A1. 2 Portfolio Composition of N-HtM Households 36

Table 2. 1 Definitions of Consumption, Income, Liquid Assets, Liquid Debts and
Net Illiquid Wealth (PSID) 51

Table 2. 2 Marginal Propensity to Consume out of Transitory Income Shocks for
Different Types of HtM Households (total consumption) 52

Table 2. 3 Marginal Propensity to Consume out of Transitory Income Shocks for
Different Types of HtM Households (nondurable) 53

Table 2. 4 Marginal Propensity to Consume out of Transitory Income Shocks for
Different Types of HtM Households (durable) 54

Table 2. 5 Marginal Propensity to Consume out of Transitory Income Shocks for Different Types of HtM Households (nonfood) 55

Table 2. 6 Marginal Propensity to Consume out of Transitory Income Shocks for Different Types of HtM Households (food) 56

Table 2. 7 Marginal Propensity to Consume out of Transitory Income Shocks for Different Types of HtM Households (utilities) 57

Table 2. 8 Marginal Propensity to Consume out of Transitory Income Shocks for Different Types of HtM Households (healthcare) 58

Table 2. 9 Marginal Propensity to Consume out of Transitory Income Shocks for Different Types of HtM Households (social sector: healthcare and education) 59

Table 3. 1 Descriptive Statistics for Core Sample. 86

Table 3. 2 Box-Cox Regression Estimates of the Out-of-Pocket Healthcare Expenditure Model ($\lambda^* \cong 0$) 88

Table 3. 3 Box-Cox Regression Estimates of the Out-of-Pocket Healthcare Expenditure Model (lambda model) ($\lambda^* \cong 0$) 89

Table 3. 4 Box-Cox Regression Estimates of the Out-of-Pocket Healthcare Expenditure Model (left-hand-side–only model) ($\lambda^* \cong 0$) 90

Table 3. 5 Box-Cox Regression Estimates of the Out-of-Pocket Healthcare Expenditure Model (right-hand-side–only model) ($\lambda^* \cong 0$) 91

Table A 3. 1 Household Head Age Group Distribution 92

Table A 3. 2 Distribution of Years of Schooling of Household Head 92

Table A 3. 3 Distribution of Average Monthly Income of Households 93

Table A 3. 4 Distribution of Wealth Holding 93

Table A 3. 5 Distribution of Net Savings 94

Table A 3. 6 Distribution of Marital Status 94

Table A 3. 7 Distribution of Number of Sick Days of RP Households 95

Table A 3. 8 Distribution of Number of Family Members of RP Households Taking any Drug 95

LIST OF FIGURES

FIGURE PAGE

Figure 1. 1 Distribution of Liquid Wealth to Monthly Income Ratios 27

Figure 1. 2 Fraction of Hand-to-Mouth (HtM) Households, United States...................... 28

Figure 1. 3 Share of HtM Households among Homeowners by Leverage Ratio 29

Figure 1. 4 Fraction of HtM Households, United States, Alternate Definitions............... 30

Figure 1. 5 Age Profile of Fraction of IP-HtM, NIP-HtM, and W- HtM Households 31

Figure 1. 6 Age Profile of the IP-HtM, NIP-HtM, and W- HtM, United States, by Demographic Characteristics 31

Figure 1. 7 Age Profile of the Portfolio Composition of the IP-HtM, NIP-HtM, and W- HtM Households 33

Figure 1. 8 Income and Portfolio Composition of different HtM Households over the Years 34

INTRODUCTION

This dissertation is comprised of three distinct yet related essays. All three essays are focused on empirical studies of macroeconomic analysis of development. In particular, I focus on the analysis of different characteristics of resource constrained households and how they react to various economic shocks. In the first two essays, I use data from the United States households for defining different groups of resource constrained households on the basis of the type of wealth they hold, deriving their demographic characteristics and their consumption reaction to transitory income shocks. In the third essay, I use a survey of a resource constrained community from a developing country, Bangladesh, to determine the factors that affect their households' healthcare expenditure.

In the first essay, I define a new category of households, the indebted poor hand-to-mouth (IP-HtM), and analyze its characteristics in relation to other types of households. Currently, the economics literature splits households into different categories depending on the type of wealth they hold (Kaplan & Violante, 2010; Kaplan, Violante, & Weidner, 2014). The categories of wealth under consideration are net liquid wealth, which is the difference between liquid assets (checking and savings accounts, stocks, bonds, etc.) and liquid debts (student loans, credit cards, etc.) and net illiquid wealth (net value of mortgages, private retirement accounts, etc.). According to this classification, hand-to-mouth (HtM) households are split into poor hand-to-mouth (P-HtM), those that hold little or no liquid wealth and no illiquid wealth; wealthy hand-to-mouth (W-HtM), those that hold no liquid wealth but sizable amounts of illiquid wealth; and not hand-to-mouth (N-HtM), those that hold both liquid and illiquid wealth. This breakdown is important to accurately capture how different categories of households react to income shocks.

I argue that this classification is missing important features related to the behavior of indebted households and further split the P-HtM households into two different subcategories that lack definition and separate analysis in the economics literature. First, I define indebted poor hand-to-mouth (IP-HtM) as the group of households that hold negative net illiquid wealth. Second, I define not indebted poor hand-to-mouth (NIP-HtM) as those households that do not hold any illiquid wealth. Using the Survey of Consumer Finances (SCF) and the Panel Study of Income Dynamics (PSID) data, I find that about 0.6 percent to 1.4 percent of total households (more than 3 million people) in the United States are IP-HtM and have debts in illiquid wealth (negative net illiquid wealth). This number increases to about 3 percent during the Great Recession of 2008-2009, followed by a decrease during the recovery period. In addition, on average about 6 percent of the P-HtM households are IP-HtM, and the rest are NIP-HtM. Moreover, in the PSID data, the maximum share of IP-HtM households is White with a geographical concentration in the southern portion of the United States.

I show that the age profile of IP-HtMs by demographic characteristics exhibits almost the same pattern as W-HtM. This suggests that one cannot assimilate IP-HtM households into the P-HtM group. However, this group does not fit into the category of W-HtM households either since the portfolio composition of the indebted household is dissimilar to that of the W-HtM. Therefore, IP-HtM households warrant their own distinct status and behavior analysis in the literature.

If the first essay focused on the definition and description of the demographic characteristics of IP-HtM, the second essay focuses on the analysis of the behavior of these households. In the second essay, I describe how total consumption and different items of consumption such as food, nonfood, durable and nondurable goods of IP-HtM households react to a transitory income change. Moreover, I discuss the marginal propensity to consume (MPC) for the social sector, healthcare, education, and utilities, which are different components of nonfood items. I use a longitudinal data set that includes information on income, consumption, and liquid and illiquid wealth at the household level that is necessary to estimate the MPCs. I use the 9 waves of pooled data (1999–2015) from the PSID survey on the United States household portfolios.

Using the methodology proposed by Blundell, Pistaferri, and Preston (2008), Kaplan and Violante (2010), and Kaplan et al. (2014), I estimate the consumption response to transitory changes in income. Unlike these studies, I use the updated sample periods with enriched data, estimate the transmission coefficients of income shocks to consumption for IP-HtM households, and find the MPCs separately for other types of HtM households. These two empirical analyses differentiate this study from Blundell et al. (2008) and Kaplan et al. (2014).

In data, results show that in the baseline specification, MPC of the total consumption for the IP-HtM households is 0.97. However, it is 0.42, 0.23, 0.48, 0.71, and 0.62 for nondurable, durable, nonfood, food, and utilities, respectively. In comparing these results to the responses of P-HtM, NIP-HtM, and W-HtM households, I find that the consumption of IP-HtM households is the most responsive (highest MPC) for all consumption items except durables, health care, and social sector expenditure in the baseline specification. This suggests that the government can obtain the maximum effectiveness of its stimulatory policies for the IP-HtM households. This study can help government design and execute the fiscal policies directing the highest stimulatory effect during economic slowdown.

In the third essay, I investigate the determinants of healthcare expenditure of a resource-constrained community using flexible Box-Cox model regression methods and cross-sectional micro-level household data. Resource-constrained households like those of working-class population live from hand to mouth, and they spend a large share of their earnings on their basic needs. They do not have enough money to pay for the necessary healthcare services. They might decrease their healthcare spending if there is any rise in out-of-pocket payment on healthcare expenditures, and even small copayments might reduce the possibility of receiving required healthcare. Healthcare providers can provide services more effectively to such low-income households, like those of day labors, if they know the factors of healthcare spending among this group of households.

For this study, I use a 2013 survey of rickshaw pullers (RP) in Dhaka, Bangladesh. Considering their poor social and economic status, type of service to the economy, lack of access to high-quality healthcare, lack of human and physical capital, and so on, RP represent a resource-constrained community in a developing country.

I find that income, distance of residence from healthcare center/hospital, age of household head, and duration of illness episode are the significant factors of healthcare utilization for a resource-constrained community. The healthcare income elasticity of about 0.55 implies that healthcare is like a normal and necessary good. How healthcare expenditure in this community reacts to changes in income level and other determinants is also relevant to health policy because healthcare is a necessity in the “basic needs” theory of economic development. This group of populations in developing countries have unmet healthcare needs. This study discusses the implications for sustainable basic healthcare development policies for the marginalized households in society.

CHAPTER 1

THE INDEBTED HAND-TO-MOUTH

1.1 Introduction

The economics literature splits households into different categories depending on the type of wealth they hold (Kaplan & Violante 2010; Kaplan, Violante, & Weidner 2014). The categories of wealth under consideration are net liquid wealth, which is the difference between liquid assets (checking and savings accounts, stocks, bonds etc.) and liquid debts (student loans, credit cards etc.) and net illiquid wealth (net value of mortgages, private retirement accounts etc.). According to this classification, hand-to-mouth (HtM) households are split into poor hand-to-mouth (P-HtM), those that hold little or no liquid wealth and no illiquid wealth, wealthy hand-to-mouth (W-HtM) those that hold no liquid wealth but sizable amounts of illiquid wealth, and not hand-to-mouth (N-HtM) households, those that hold both liquid and illiquid wealth. This breakdown is important to accurately capture how different categories of households react to income shocks.

I argue that this classification is missing important features related to the behavior of indebted households and further split the P-HtM households into two different subcategories that lack definition and separate analysis in the economics literature. First, I define indebted poor hand-to-mouth (IP-HtM) as the group of households that hold negative net illiquid wealth.[1] Second, I define not indebted poor hand-to-mouth (NIP-HtM) as those households that do not hold any illiquid wealth.

[1] Gerardi, Herkenhoff, Ohanian, and Willen (2018) show that focusing on housing as the main illiquid assets, contrary to what standard models of strategic default would imply, nearly all very low equity borrowers remain current on their payments, and therefore preserve their illiquid assets. This finding

I find that in terms of demographic characteristics, IP-HtMs are more similar to W-HtM than to P-HtM households, the category into which they currently fall in the literature. This suggests that one cannot integrate IP-HtM households into the P-HtM group. On the other hand, this group does not fit into the category of W-HtM households since the portfolio composition of the indebted household is quite different from that of the W-HtM. Therefore, it makes more sense not to integrate the IP-HtM households into either the P-HtM or the W-HtM households; rather, IP-HtM households deserve their own separate status and behavior analysis in the literature.

I compiled pooled information from the *Household Dataset* for the period of 1989-2016 at the Survey of Consumer Finances (SCF) during the course of my research from 2016 through 2018. During that same period, I collected pooled data from the *Household and Individual Dataset* for the period of 1999-2015 at the Panel Study of Income Dynamics (PSID). I used the SCF 10 waves of pooled data (1989–2016) of the United States to document the share of IP-HtM households and analyze demographic characteristics, and the portfolio composition of IP-HtM households. I used the 9 waves of pooled data (1999–2015) from the PSID to observe the share of IP-HtM on the basis of race and geographical location, and the persistence of IP-HtM status over household life cycle.

Using the SCF and the PSID data, I find that about 0.6 percent to 1.4 percent of total households (more than 3 million people) in the United States are IP-HtM, and have debts in illiquid wealth (negative net illiquid wealth). This number increases to about 3

includes about 80 percent of households that need to cut their consumption to subsistence levels to make their mortgage payments.

percent during the Great Recession of 2008-2009, followed by a decrease during recovery. In addition, on average about 6 percent of the P-HtM households are IP-HtM and the rest are NIP-HtM. Moreover, in the PSID data, the maximum share of IP-HtM households is White with a geographical concentration in the southern portion of the United States.

The remainder of this paper is organized as follows: section two presents the literature review, section three discusses the selected the sample and identifies IP-HtM households in the data, section four identifies the share of IP-HtM households in the United States data, section five explores demographics and portfolio composition of IP-HtM, section six shows the share of IP-HtM households based on race and regions in PSID Data, section seven describes the status persistence of IP-HtM households, and the final section concludes.

1.2 Literature Review

Campbell and Mankiw (1989), Huggett (1996), Aiyagari (1994), Ríos-Rull (1995), and Krusell and Smith (1998) used data on net worth to determine HtM behavior. Justiniano, Primiceri, and Tambalotti (2015), Eggertson and Krugman (2012), and Gali, Lopez-Salido, and Valles (2007), among others, used this type of model to study macroeconomic dynamics around the Great Recession.

Kaplan et al. (2014) claimed that using data on net worth to estimate HtM behavior is misleading as this oversights what they call the W-HtM households, that is, households that have significant amounts of net worth or positive assets, but in an illiquid form. This is also supported by Cui and Feng (2017). They documented that nearly 17 percent of households in China are HtM, among them 10 percent are P-HtM and 90 percent are W-HtM. They also claimed that HtM in China mostly consist of the W-HtM, who would be ignored by the traditional net worth measure.

A two-asset model (liquid asset and illiquid asset) developed by Kaplan et al. (2014) instead of using net worth to characterize a more complex dimension of HtM behavior. The illiquid asset pays a higher interest rate, but requires a transaction cost for access. Two-asset models were also used by Angeletos, Laibson, Repetto, Tobacman, and Weinberg (2001), Laibson, Repetto, and Tobacman (2003), Chetty and Szeidl (2007), Alvarez, Guiso, and Lippi (2012), Huntley and Michelangeli (2014), and Kaplan and Violante (2014a, 2014b).

Within the scope of this two-asset model, Kaplan et al. (2014) identified the N-HtM as those households that have positive liquid assets and two other types of HtM households. The P-HtM households have little or no liquid wealth and no illiquid wealth. The W-HtM counterparts also have little or no liquid wealth; however, they hold substantial volumes of illiquid assets. Even though W-HtM have positive assets and thus a positive net worth that makes them similar to N-HtM, they have a high MPC and lack the ability to exercise consumption smoothing similar to the P-HtM households. Therefore, Kaplan et al. (2014) argued that it is impossible to completely integrate W-HtM into either group and that W-HtM requires identification as a separate category of households for the purpose of economic analysis. They used the SCF and PSID for United States household data to identify the different types of HtM households. Their estimates indicate that, on average, 31 percent of United States households are HtM. Of these, approximately 10 percent are P-HtM and the rest are W-HtM. They found the similarity among the United States, the United Kingdom, and Canada in their overall share of HtM households and the breakdown between P-HtM and W-HtM. Among the euro area countries, the fraction of HtM in Germany is closer to 30 percent; however, France, Italy, and Spain have around 20 percent of HtM households. On the other hand, the total share of HtM in Australia is roughly half the fraction in the United States, the United Kingdom, and Canada. Also, 90 percent of Australia's HtM households are W-HtM. All the eight countries in their study, there are more W-HtM than P-HtM households. This share exceeds two third for the euro area countries.

Park (2017) found that the shares of N-HtM, W-HtM, and P-HtM households are 64.0 percent, 32.2 percent, and 3.8 percent respectively in South Korea. Hara, Unayama, and Weidner (2016) documented HtM households and studied their characteristics in Japanese data. They showed that the share of HtM is about 13 percent, which is much smaller than other developed countries and nearly one-quarter of them are considered as P-HtM and rest of them are W-HtM.

1.3 Data and Methodology

I use the method developed by Kaplan et al. (2014) to identify the different categories of HtM households and analyze their behavior and, thus, assume that the available savings instruments are a liquid asset (M) and an illiquid one (A).

Kaplan et al. (2014) defined a household, as N-HtM if it holds a positive amount of liquid and illiquid wealth: $M > 0$ and $A \geq 0$; as P-HtM if it does not hold any liquid or illiquid wealth: $M \leq 0$ and $A \leq 0$; and as W-HtM if it holds a sizable amount of illiquid wealth but no liquid wealth: $M = 0$ and $A > 0$.

I split P-HtM into two HtM groups: IP-HtM and NIP-HtM and define a household as IP-HtM if it has a negative amount of net illiquid wealth, $A < 0$; and as NIP-HtM if it holds zero net illiquid wealth, $A = 0$.

Let Y_{kt} denote the income of household k in pay-period t, A_{kt} denotes holdings of illiquid assets, and M_{kt} denotes average balances of liquid wealth over the pay periods. I follow the definitions of W-HtM and P-HtM households as used in Kaplan et al. (2014) and assume that resources are consumed at a constant rate and define non-credit constrained households as those whose average liquid wealth balances are positive (they do not borrow) but are equal to or less than half their earning per pay-period.

In this case a household is W-HtM if

$$A_{kt} > 0 \text{ and } 0 \leq M_{kt} \leq \frac{Y_{kt}}{2} \tag{1.1}$$

A household is P-HtM if

$$A_{kt} \leq 0 \text{ and } 0 \leq M_{kt} \leq \frac{Y_{kt}}{2} \tag{1.2}$$

I further use the criterion to identify the more minute categories of P-HtM.

A household is IP-HtM if

$$A_{kt} < 0 \text{ and } 0 \leq M_{kt} \leq \frac{Y_{kt}}{2} \tag{1.3}$$

and a household is NIP-HtM if

$$A_{kt} = 0 \text{ and } 0 \leq M_{kt} \leq \frac{Y_{kt}}{2} \tag{1.4}$$

As shown in Kaplan et al. (2014), the estimator on the number of HtM is a lower bound because some HtM household might hold, on average, liquid balances above half their earnings.[2]

I now consider the HtM household at the credit limit $-\underline{M}_{kt} < 0$ so that it consumes all its cash-on-hand for the period, plus all its available credit. Credit limit refers to the maximum amount of credit financial institutions extend to a household through a line of credit as well as the maximum amount credit card companies allow a household to spend on cards.

A household is W-HtM if

$$A_{kt} > 0, M_{kt} \leq 0 \quad \text{and} \quad M_{kt} \leq \frac{Y_{kt}}{2} - \underline{M}_{kt} \tag{1.5}$$

A household is P-HtM if

$$A_{kt} \leq 0, M_{kt} \leq 0 \quad \text{and} \quad M_{kt} \leq \frac{Y_{kt}}{2} - \underline{M}_{kt} \tag{1.6}$$

I use the criterion to identify an IP-HtM household if

$$A_{kt} < 0, M_{kt} \leq 0 \quad \text{and} \quad M_{kt} \leq \frac{Y_{kt}}{2} - \underline{M}_{kt} \tag{1.7}$$

I identify a NIP-HtM household if

$$A_{kt} = 0, M_{kt} \leq 0 \quad \text{and} \quad M_{kt} \leq \frac{Y_{kt}}{2} - \underline{M}_{kt} \tag{1.8}$$

I identify in the data the different categories of households: the W-HtM households by combining (1.1) and (1.5), the P-HtM by combining (1.2) and (1.6), the IP-HtM by combining (1.3) and (1.7), and NIP-HtM by combining (1.4) and (1.8).

Using the SCF's ten waves (1989- 2016) I identify the IP-HtM households in the United States starting with the core SCF sample and drop households whose income is

[2] A household can start a period with liquid savings, earn a certain income and end the period with zero liquid assets. This household is HtM, but by the criterion used is counted as N-HtM.

negative and those for which all income comes from self-employment and keep households where the head is 22–79 years old. The final sample has 39,395 observations over the pooled 10 sample years. The SCF survey is triennial. Table 1.1 summarizes the survey years used in the sample selection and the final sample sizes. In selecting the definition of income, I include all labor income, any government transfers that are regular inflows of liquid assets. Because of their irregular perception, I exclude interest, dividends, and other capital income. The definitions of income, liquid assets, liquid debts, and net illiquid wealth are set forth in Table 1.2. Net liquid asset is liquid assets minus liquid debts.

Table 1.3 provides some descriptive statistics on household income, liquid and illiquid wealth holdings, and portfolio composition based on the pooled 1989-2016 SCF data. The typical household portfolio structure consists of liquid wealth in the form of bank accounts and illiquid wealth in the form of housing equity and private retirement accounts. The median holdings of other financial assets such as directly held stocks, bonds, and life insurance are zero everywhere. Guiso, Halassios, and Jappelli (2002) derived similar results in their empirical studies of household portfolios. Housing equity forms most of illiquid wealth for households. About 50 percent of households have positive private retirement wealth and around 26 percent of households hold positive life insurance.

Figure 1.1 plots the distribution of liquid wealth to monthly income considering the pooled 1989-2016 SCF data. It shows that the ratio is 0 for about 4 percent of the households and about 2.5 for 6.25 percent of the households in the United States.

1.4 The Share of Indebted Hand-to-Mouth Households

I base my estimation of IP-HtM on Equations (1.3) and (1.7). In the benchmark analysis, the pay frequency was set to two weeks and the household credit limit was set to one month of income.

Figure 1.2(a) explores the fraction of HtM households in the United States population over the period 1989–2016 in SCF data and depicts the split between IP-HtM, NIP-HtM, and W-HtM. Estimates report that, on average, 0.6 percent of the United States households were IP-HtM until the 2008-2009 Great Recession. It rose to about 2 percent during the recession and started to fall during the recovery periods after 2010. Figure 1.2(a) also shows that IP-HtM was about 6 percent of the P-HtM before the recession and the proportion increased to around 14 percent during the recession. The share of IP-HtM in P-HtM started to fall after 2010 and again reached to around 6 percent in 2015. The share of all HtM households increased during the recession.

Figures 1.2(b), 1.2(c), and 1.2(d) focus on the illiquid portfolio[3] distribution (only housing wealth, other illiquid but no housing wealth[4], both other and housing wealth) (Table 1.2) of the different categories of HtM. Figure 1.2(b) plots the share of IP-HtM households that own housing, non-housing illiquid wealth, or both. About 90 percent of IP-HtM households have both, around 10 percent have positive housing but no nonhousing illiquid wealth, and no household has only nonhousing illiquid wealth. Figure 1.2(c) shows that almost all NIP-HtM households have only nonhousing illiquid wealth, however overall their net illiquid wealth is zero. Figure 1.2(d) shows that around 28

[3] Here only illiquid assets (no illiquid debts) are under consideration in portfolio composition analysis.

[4] All other components of illiquid wealth except housing.

percent of W-HtM households have both housing wealth and other types of illiquid wealth, about 27 percent have positive housing but no nonhousing illiquid wealth, and approximately 45 percent have only nonhousing illiquid wealth. Not surprisingly, I notice the highest share of W-HtM with both housing wealth and other types of illiquid wealth in 2007.

Figure 1.3 shows that about 30 percent of households whose leverage ratio is higher than 1 is IP-HtM, as regular mortgage payments absorb a significant fraction of disposable income and leave households little or no liquid savings.

Robustness

Figure 1.4 and Table 1.4 report sensitivity analyses. Figure 1.4(a) plots the shares of IP-HtM, NIP-HtM, and W-HtM households weighted by income. The weighted fraction of IP-HtM, NIP-HtM, and W-HtM households is smaller than its unweighted counterpart. Figure 1.4(b) shows the HtM shares when considering the pay period as 1 month instead of 2 weeks: the fraction of IP-HtM, NIP-HtM, and W-HtM household increases by 17, 18, and 34 percent, respectively (the fraction of IP-HtM, NIP-HtM, and W-HtM increase by 0.1, 1.9, and 5.2 percentage points, respectively). Likewise, the fifth line of Table 1.4 reports that when setting the pay period to 1 week, the share of IP-HtM and NIP-HtM household drops correspondingly by 17 percent and 13 percent.

Figure 1.4(c) shows that the fraction of IP-HtM households drops by 33 percent, with only a 3 percent decrease in NIP-HtM households if using the self-reported credit limit instead of 1 month of income as a credit limit. Lastly, Figure 1.4(d) explores that if vehicles are included as illiquid wealth, about half of the IP-HtM and NIP-HtM move into the W-HtM group.

1.5 Demographics and Portfolio Composition of Indebted Hand-to-Mouth Households

Figure 1.5 depicts the share of the different HtM households: IP-HtM, NIP-HtM, and W-HtM by age. The majority of observations of NIP-HtM household behavior occur in the early stages of the life cycle, at which time most people do not have any type of illiquid assets. The fraction of NIP-HtM households drops abruptly until age 30, as they acquire illiquid assets, and keeps dropping steadily over the life cycle until reaching around 6 percent at age 79. Figure 1.5 shows that the age profile of the fraction of W-HtM households is prominently hump-shaped: it peaks at around age 38, and remains above 12 percentage points over the life cycle. Focusing on the IP-HtM households, there is no apparent age trend as the share of IP-HtM is consistently around 0.6 percent of the population for all age groups.

Figure 1.6 focuses on different demographic characteristics by age for the HtM households. Figure 1.6(a) indicates that IP-HtM and W-HtM groups have, on average, two more years of education than NIP-HtM households. In Figure 1.6(b), I cannot differentiate between IP-HtM and W-HtM households in terms of marital status. However, the NIP-HtM households are 35 percent less likely to be married. In terms of having children, Figure 1.6(c) shows that IP-HtM, NIP-HtM, and W-HtM households are indistinguishable. Figure 1.6(e) indicates that W-HtM households are less likely to have a member of their household unemployed than both categories of P-HtM.

Figure 1.6(d) reveals that, on average, IP-HtM households have a higher median income during the working years than NIP-HtM households. The interesting outcome is that the IP-HtM group is very similar to the W-HtM in terms of their income path, the median income for NIP-HtM is about $15,000, while for W-HtM and IP-HtM it is about $20,000 higher, following a hump-age profile with the peak at about $40,000. IP-HtM and W-HtM have very similar patterns regarding their access of governments benefits, both in terms of what proportion of their income is due to government benefits (Figure 6(f)) and the fraction of households that receive governments benefits (Figure 6(g)). There are about 20 percentage points more NIP-HtM than W-HtM and IP-HtM households that receive some form of government benefits and it is striking to notice that in most respects IP-HtM are more similar with W-HtM than with NIP-HtM households. In fact, out of the seven demographic characteristics analyzed, for five of them IP-HtM are similar to W-HtM and dissimilar from NIP-HtM, and for one a pattern cannot be observed. Only for one aspect are IP-HtM similar to NIP-HtM and different from W-HtM.

Figure 1.7 reports the age profile of the portfolio composition of IP-HtM, NIP-HtM, and W-HtM households. Figure 1.7(a) explores the finding that median net liquid wealth holdings are zero at virtually every age for both the NIP-HtM and W-HtM households. Median net liquid wealth for IP-HtM households is, on an average, negative. Figure 1.7(b) shows that IP-HtM households are indebted in illiquid wealth whereas the W-HtM households have substantial amounts of illiquid wealth. Figures 1.7(c) and 1.7(d) plot the mean net liquid and illiquid wealth composition of the three HtM groups. Figure 1.7(c) reveals that the IP-HtM and W-HtM households have negative mean net liquid wealth whereas it is zero for the NIP-HtM group across the life cycle. Figure 1.7(d) explores the similar pattern of age profile as observed in Figure 1.7(b) for all HtM groups. Figure 1.7(e) shows that the IP-HtM households have a higher mean fraction of illiquid wealth in housing in all stages of the life cycle. Figure 1.7(f) shows that the IP-HtM group holds a negative mean fraction of illiquid wealth in retirement accounts whereas the fraction falls steadily for the W-HtM through their life cycle. Figures 1.7(e) and 1.7(f) show that, in fact, all the illiquid wealth of the IP-HtM households is in housing, and retirement is a very negligible part of their portfolio.

Figure 1.8 articulates the income and balance-sheet composition of IP-HtM, NIP-HtM, and W-HtM households over the years. Figures 1.8(a) and 1.8(b) explore that the IP-HtM and W-HtM groups have higher median and mean income than the NIP-HtM households all over the waves. One can also see that the mean and median income of IP-HtM fluctuate more than the W-HtM households. Figures 1.8(c) and 1.8(d) show the median and mean net liquid wealth of different HtM households. The median net liquid wealth for IP-HtM is negative while, on average, it is zero for the other HtM groups. Though the mean liquid wealth is zero for the NIP-HtM, it is negative for other HtM households. Figures 1.8(e) and 1.8(f) reveal that the median and mean illiquid wealth are negative for the IP-HtM, zero for the NIP-HtM, and significantly positive for the W-HtM in all waves used.

1.6 The Share of Indebted Hand-to-Mouth Households Based on Race and Regions

I begin with the PSID core sample. Eliminated are households with missing values on education of head, race of head, or region where head grew up. Also dropped are households whose income grow more than 500 percent, fall by more than 80 percent, or are below $100 and top-coded income. I also drop the households where the head is less than 30 or more than 57 years old. The final sample has 50,475 observations over the pooled 9 sample years. Table 1.5 displays the definitions of income, liquid assets, liquid debts, and net illiquid wealth. Net liquid asset is liquid assets minus liquid debts. The definitions of income and wealth and the IP-HtM status indicators are the same as mentioned in Section 3. The pay period is set at every two weeks and the credit limit at 1 month of income.

Table 1.6 shows that 1.40 percent of households are IP-HtM in my PSID pooled 1999-2015 waves in the United States. Table 1.6 also reports that 19.6 percent of households are NIP-HtM and about 24 percent of households are W-HtM.

Table 1.7 shows that the maximum share of the IP-HtM households are White, whereas Black households have the majority percentage in cases of P-HtM and NIP-HtM. The highest percentage of W-HtM households is White. Table 1.8 reveals that the highest percentage of all types of HtM households is from the southern part of the United States.

1.7 Status Persistence of Indebted Hand-to-Mouth Households in PSID Data

Tables 1.9 and 1.10 analyze the persistence of the status of the households under consideration in PSID data. Table 1.9 depicts the forward transient state of different HtM and N-HtM households. Row 1 of Table 1.9 reports that about 1, 26, 28, and 45 percent of IP-HtM move to IP-HtM, NIP-HtM, W-HtM, and N-HtM, respectively, in the following wave. Row 2 shows that about 1, 25, 26, and 48 of NIP-HtM households move to IP-HtM, NIP-HtM, W-HtM, and N-HtM correspondingly in the next wave. Row 3 displays the transient state of W-HtM and shows the similar pattern of transition to that of NIP-HtM. Row 4 shows that about 2, 25, 25, and 49 of N-HtM households shift to IP-HtM, NIP-HtM, W-HtM, and N-HtM, respectively, in the following wave. Given that

IP-HtM represent at the most 3 percent of all the households in the sample, it is not surprising that a small percentage of NIP-HtM, W-HtM, and N-HtM end up being IP-HtM in the next wave. It is interesting to note that the IP-HtM is very transient, as only 1.1 percent of the affected households stay this way, and, in fact, about 45 percent of them end up being N-HtM. The probability of IP-HtM becoming N-HtM is, however, the smallest out of all the categories of households under consideration.

Table 1.10 reveals the probability of backward transient state of different HtM and N-HtM households. Column 1 of Table 1.10 explores that 1, 21, 26, and 52 of IP-HtMs were in the group of IP-HtM, NIP-HtM, W-HtM, and N-HtM, respectively, in the previous wave. Column 2 shows that about 2, 24, 25, and 49 of NIP-HtM belonged to IP-HtM, NIP-HtM, W-HtM, and N-HtM correspondingly in the last wave. Column 3 reports that about 2, 24, 27, and 47 of W-HtM belonged to IP-HtM, NIP-HtM, W-HtM, and N-HtM, respectively in the previous wave. Column 4 displays that about 1.5, 23, 26, and 49 of N-HtM belonged to IP-HtM, NIP-HtM, W-HtM, and N-HtM correspondingly in the last wave.

1.8 Conclusion

This paper examines the IP-HtM households previously ignored in the literature using the share of IP-HtMs in the United States. I find that about 1 percent of total households (more than 3 million people) and 6 percent of the P-HtM in the United States are IP-HtM in the pooled SCF 1989-2016 data. However, this increased to around 3 percent during the Great Recession in 2008-2009 and fell during the recovery. I find almost the same share of IP-HtM households in the PSID survey data.

In previous studies, IP-HtM households were a share of P-HtM households. Nevertheless, I show that one cannot integrate IP-HtM households into the P-HtM group since demographic characteristics are far more similar to W-HtM than NIP-HtM. In fact, for more than three quarters of the characteristics analyzed, IP-HtMs are virtually indistinguishable from the W-HtMs. However, one cannot assimilate IP-HtM with W-HtM because their portfolio composition is different from W-HtM. Therefore, IP-HtM households must have their own separate status in the literature.

Overall, this study reveals three main findings by analyzing United States data. First, I find that between 0.6 and 3 percent of United States households are IP-HtM. Second, in terms of demographic characteristics, IP-HtM households are more similar to the W-HtM rather than to the P-HtM, the category in which they were previously assimilated. Third, the highest percentage of all HtM households is concentrated in the southern part of the United States and the maximum share of IP-HtMs is among White households.

TABLES

Table 1. 1 Summary Information on the Survey Data Used

Survey years	SCF 1989-2016
Initial sample size	47,776
Exclusions	
Not age 22–79	2,858
Negative income	10
All income from self-employment	5,513
Final sample size	39,395

Source: Author's calculations based on the pooled 1989–2016 Survey of Consumer Finances (SCF) United States. See text for full description of the data.

Table 1. 2 Definitions of Income, Liquid assets, Liquid Debts, and Net Illiquid wealth (SCF)

Items	Components
Income	Gross wages and salaries, self-employment income, regular private transfers such as child support and alimony, public transfers such as unemployment benefits, food stamps, and Social Security Income (SSI), and regular income from other sources excluding investment income.
Liquid assets	Checking and savings accounts, money markets and call accounts, directly held mutual funds, stocks, corporate bonds and government bonds.
Liquid debts	Summation of all credit card balances that accrue interest after the most recent payment.
Net illiquid wealth	Value of housing, residential and non-residential real estate, net of mortgages and home equity loans, private retirement accounts (such as 401(k)s, IRAs, thrift accounts, and future pensions), cash value of life insurance policies, certificates of deposit, and savings bonds.

Table 1. 3 Household Income, Liquid and Illiquid Wealth Holdings, and Portfolio Composition

	Median	Mean	Fraction Positive
Income (age 22-59)	30,984	49,279	0.988
Net worth	77,136	334,083	0.904
Net liquid wealth	2,787	96,595	0.783
Cash, checking, saving, MM accounts	3,333	27,024	0.909
Directly held stocks	0	32,925	0.167
Directly held bonds	0	8,607	0.023
Revolving credit card debt	0	1,670	0.429
Net illiquid wealth	67,370	23,7488	0.787
Housing net of mortgages	40,714	149,176	0.66
Retirement accounts	153	73,233	0.503
Life insurance	0	8,193	0.256

Source: Author's calculations based on the pooled 1989–2016 Survey of Consumer Finances (SCF) United States, age limit 22-79. See text for full description of the data.

Table 1. 4 Robustness Results for Fraction HtM in Each HtM Category

	P-HtM[i]	IP-HtM[i]	NIP-HtM[i]	W-HtM[i]
Baseline	0.109	0.006	0.103	0.153
Financially fragile households[a]	0.175	0.009	0.167	0.305
Reported credit limit	0.104	0.004	0.100	0.115
1-year income credit limit	0.094	0.003	0.091	0.094
Weekly pay period	0.094	0.005	0.090	0.122
Monthly pay period	0.129	0.007	0.122	0.205
Higher illiquid wealth cutoff[b]	0.117	0.117	0.000	0.145
Retirement account as liquid for 60+[c]	0.109	0.006	0.103	0.145
Businesses as illiquid assets[d]	0.103	0.005	0.097	0.154
Direct as illiquid assets[e]	0.108	0.006	0.103	0.169
Other valuables as illiquid assets	0.105	0.006	0.099	0.157
Excludes cc puzzle households	0.151	0.006	0.145	0.143
Home Equity Line of Credits (HELOCs) as liquid debt	0.108	0.005	0.102	0.154
Usual income	0.110	0.007	0.104	0.163
Disposable income - Reported[f]	0.108	0.006	0.103	0.151
Disposable income - Single[f]	0.107	0.006	0.102	0.150
Committed consumption-beginning of period[g]	0.090	0.005	0.086	0.133
Committed consumption-end of period[h]	0.139	0.00	0.131	0.214

Source: Author's calculations based on United States SCF pooled 1989–2016. See text for full description.
a. Includes those households within $2,000 in liquid assets of their income threshold as HtM.
b. Requires households to have above $1,000 in illiquid assets to be considered W-HtM.
c. Puts retirement accounts into liquid wealth for households above age 60.
d. Drops the self-employment income sample selection and adds business assets to illiquid wealth and self-employment income to income.
e. Classifies directly held mutual funds, stocks, and corporate and government bonds as illiquid assets.
f. Subtracts federal income taxes estimated from NBER's TAXSIM from income. Disposable income (reported) assumes that each household files its actual marital status and number of children as dependents; disposable income (single) assumes that every household files as single with no dependents.
g. Assumes the household's committed consumption is incurred at the beginning of the period.
h. Assumes the household's committed consumption is incurred at the end of the period.
i. P-HtM = poor - HtM; IP-HtM = indebted poor - HtM; NIP-HtM = not indebted poor - HtM; W-HtM = wealthy - HtM

Table 1. 5 Definitions of Consumption, Income, Liquid Assets, Liquid Debts and Net Illiquid Wealth (PSID)

Items	Components
Income	Government transfers plus labor earnings of a household.
Liquid assets	Money market funds, value of checking and savings accounts, certificates of deposit, savings bonds, and treasury bills, together with directly held shares of stock in publicly held corporations, investment trusts or mutual funds.
Liquid debts	Value of debts such as student loans, medical or legal bills, credit cards, and personal loans.
Net illiquid wealth	Summation of the value of private annuities or IRAs, value of home equity, net value of other real estate, value of other investments in trusts or estates, bond funds, and life insurance policies.

Table 1. 6 Fraction of HtM Households, PSID pooled 1999-2015 Waves, United States

Year	P-HtM	IP-HtM	NIP-HtM	W-HtM
1999	0.174	0.007	0.167	0.234
2001	0.170	0.007	0.163	0.260
2003	0.178	0.008	0.169	0.271
2005	0.183	0.008	0.175	0.281
2007	0.182	0.006	0.176	0.269
2009	0.252	0.029	0.224	0.251
2011	0.244	0.031	0.213	0.203
2013	0.265	0.025	0.240	0.180
2015	0.246	0.010	0.236	0.206
Mean	0.210	0.014	0.196	0.239

Table 1. 7 Percentage of IP-HtM, NIP-HtM, and W-HtM Households Based on Races

	P-HtM (%)	IP-HtM (%)	NIP-HtM (%)	W-HtM (%)
White	33.52	53.41	32.29	55.74
Black	59.41	37.03	60.79	36.89
Others	7.08	9.56	6.92	7.37

Source: Author's calculations based on the United States Panel Study of Income Dynamics (PSID) pooled 1999-2015 waves, age limit 30-57. See text for full description.

Table 1. 8 Percentage of IP-HtM, NIP-HtM, and W-HtM Households Based on Regions

	P-HtM (%)	IP-HtM (%)	NIP-HtM (%)	W-HtM (%)
Northeast	10.52	8.06	10.72	12.82
Midwest	21.87	22.78	21.79	24.08
South	48.94	43.95	49.35	47.67
West	18.66	25.20	18.14	15.44

Source: Author's calculations based on the United States Panel Study of Income Dynamics (PSID) pooled 1999-2015 waves, age limit 30-57. See text for full description.

Table 1. 9 Probability of Forward Transient state of HtM Households

→	IP-HtM	NIP-HtM	W-HtM	N-HtM
IP-HtM	0.011	0.261	0.278	0.449
NIP-HtM	0.013	0.246	0.261	0.479
W-HtM	0.014	0.241	0.262	0.482
N-HtM	0.016	0.247	0.246	0.490

Source: Author's calculations based on the United States Panel Study of Income Dynamics (PSID) pooled 1999-2015 waves, age limit 30-57. See text for full description.

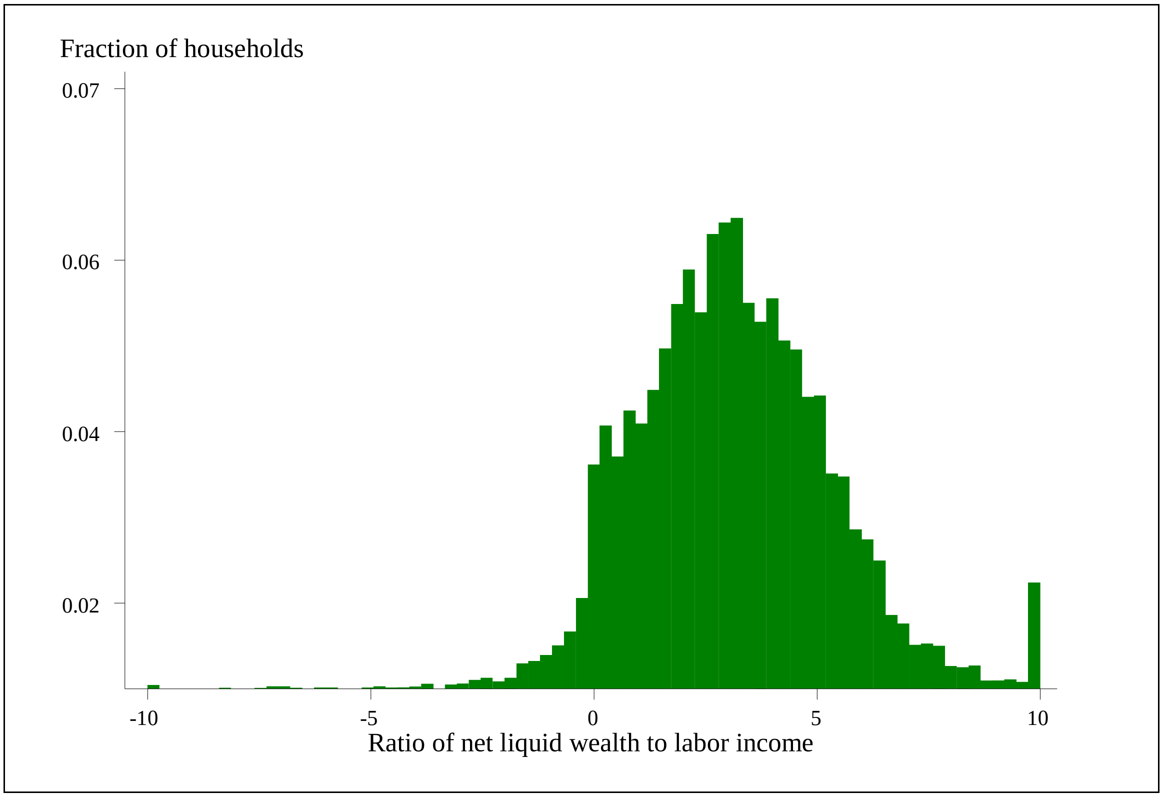
Table 1. 10 Probability of Backward Transient state of HtM Households

→	IP-HtM	NIP-HtM	W-HtM	N-HtM
IP-HtM	0.012	0.017	0.018	0.015
NIP-HtM	0.207	0.237	0.243	0.234
W-HtM	0.256	0.254	0.267	0.258
N-HtM	0.524	0.491	0.472	0.493

Source: Author's calculations based on the United States Panel Study of Income Dynamics (PSID) pooled 1999-2015 waves, age limit 30-57. See text for full description.

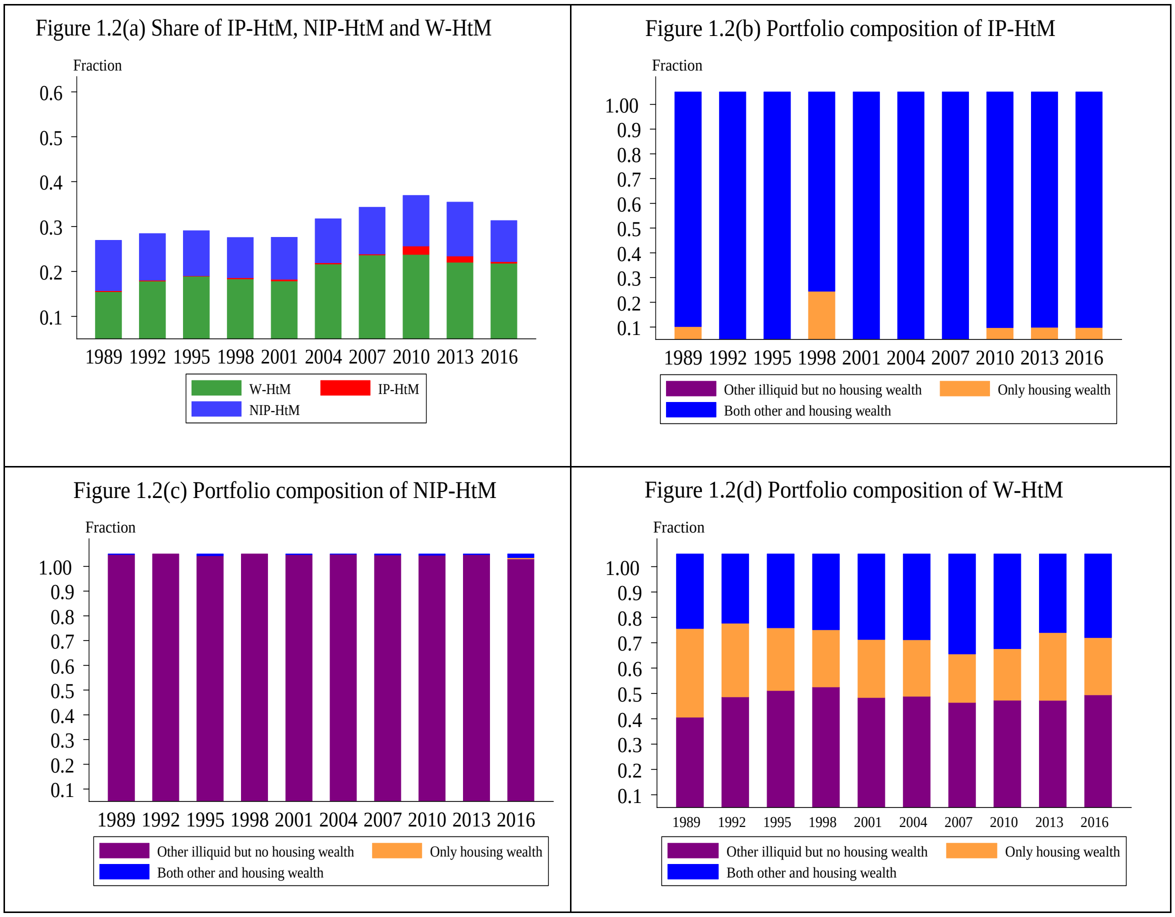
FIGURES

Figure 1. 1 Distribution of Liquid Wealth to Monthly Income Ratios



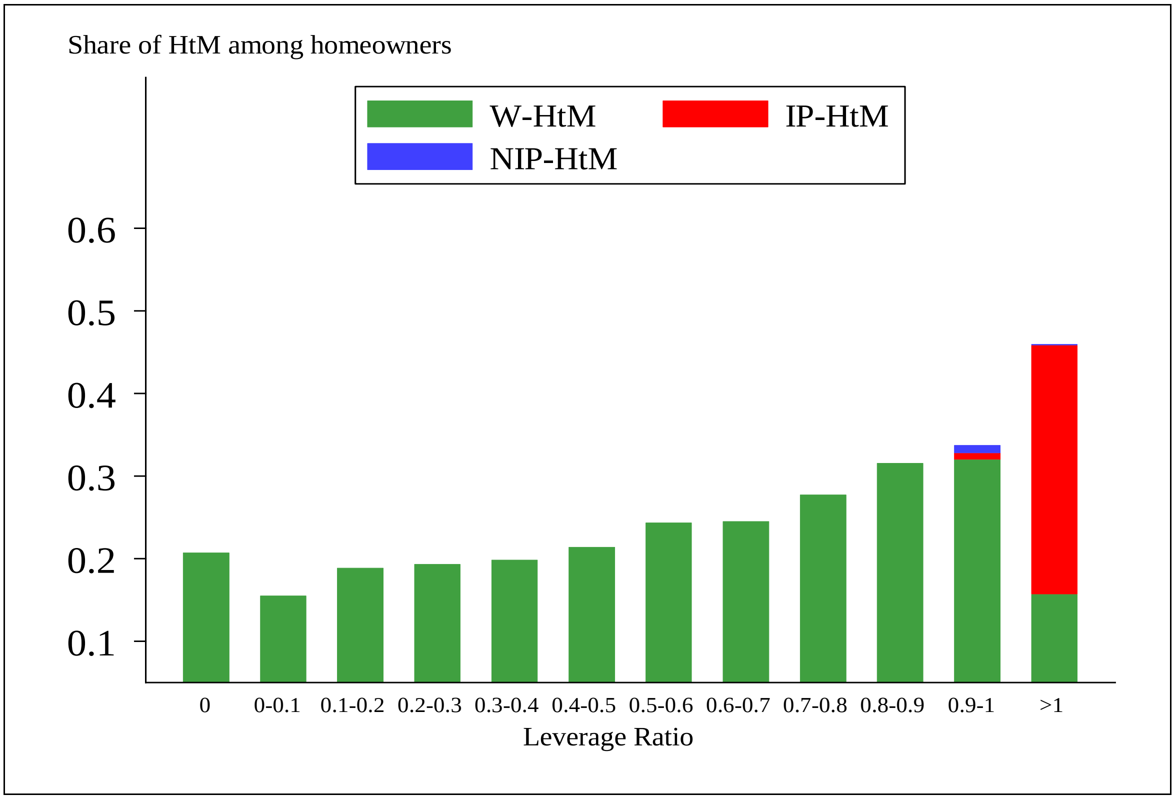
Source: Author's calculations based on the pooled 1989–2016 Survey of Consumer Finances (SCF), United States, age limit 22-79. See text for full description of the data.

Figure 1. 2 Fraction of Hand-to-Mouth (HtM) Households, United States



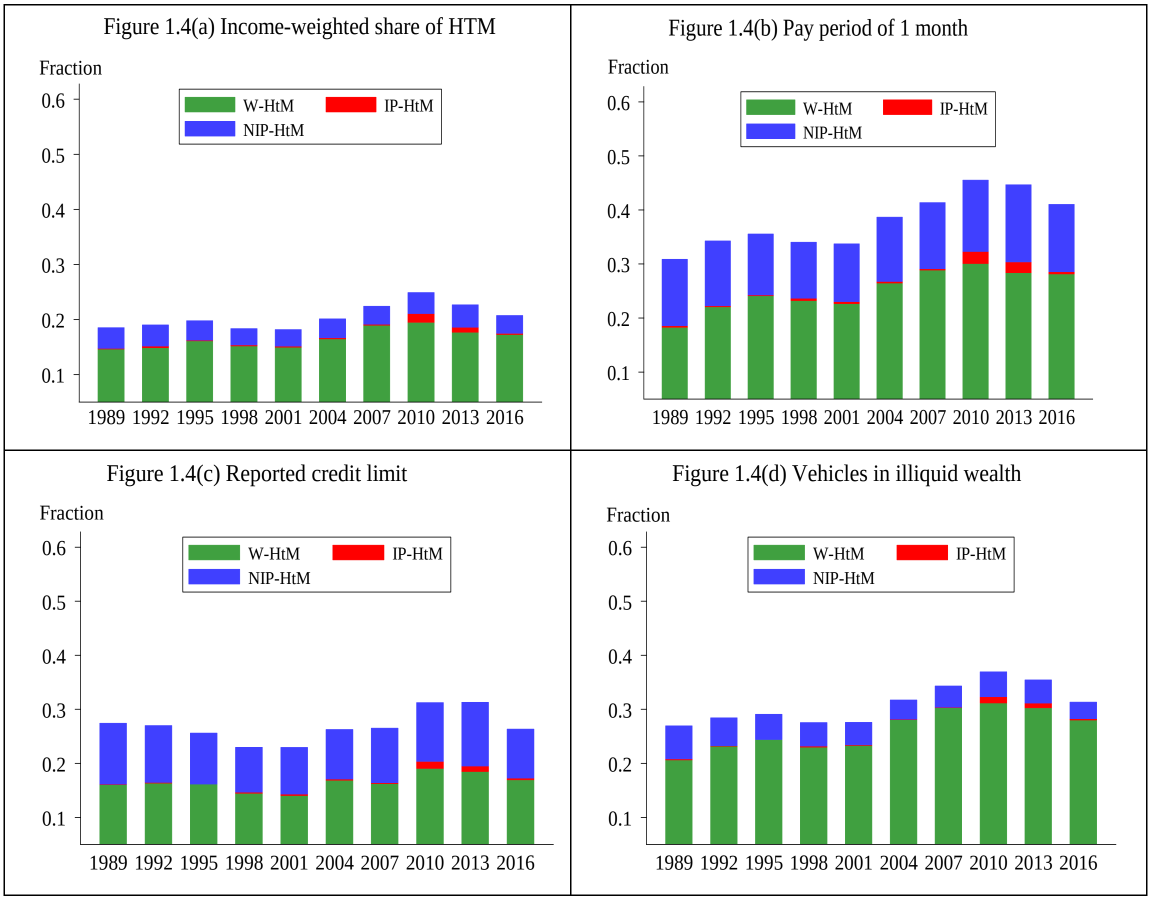
Source: Author's calculations based on the pooled 1989–2016 Survey of Consumer Finances (SCF), United States, age limit 22-79. See text for full description of the data.

Figure 1. 3 Share of HtM Households among Homeowners by Leverage Ratio



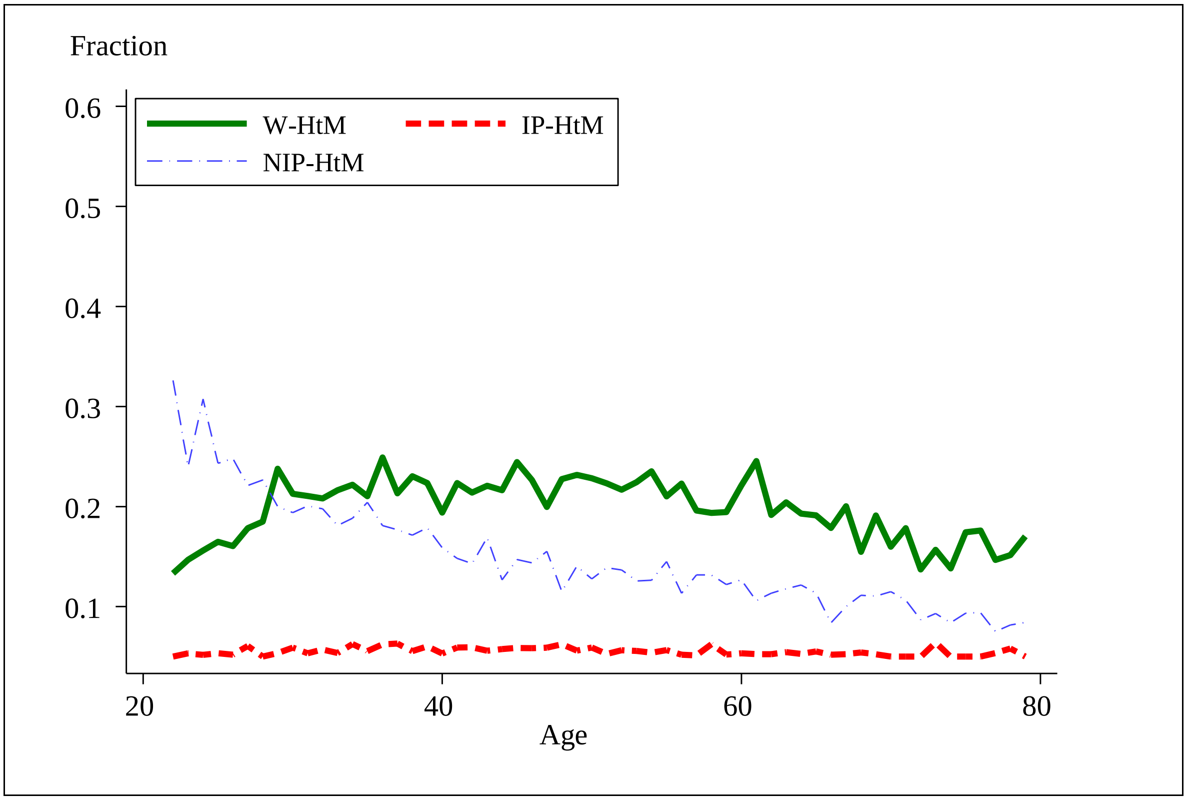
Source: Author's calculations based on the pooled 1989–2016 Survey of Consumer Finances (SCF), United States, age limit 22-79. See text for full description of the data.

Figure 1. 4 Fraction of HtM Households, United States, Alternate Definitions



Source: Author’s calculations based on the pooled 1989–2016 Survey of Consumer Finances (SCF), United States, age limit 22-79. See text for full description of the data.

Figure 1. 5 Age Profile of Fraction of IP-HtM, NIP-HtM, and W- HtM Households



Note: Age refers to that of the head of the household. Author's calculations based on the pooled 1989–2016, Survey of Consumer Finances (SCF) United States, age limit 22-79. See text for full description of the data.

Figure 1. 6 Age Profile of the IP-HtM, NIP-HtM, and W- HtM, United States, by Demographic Characteristics

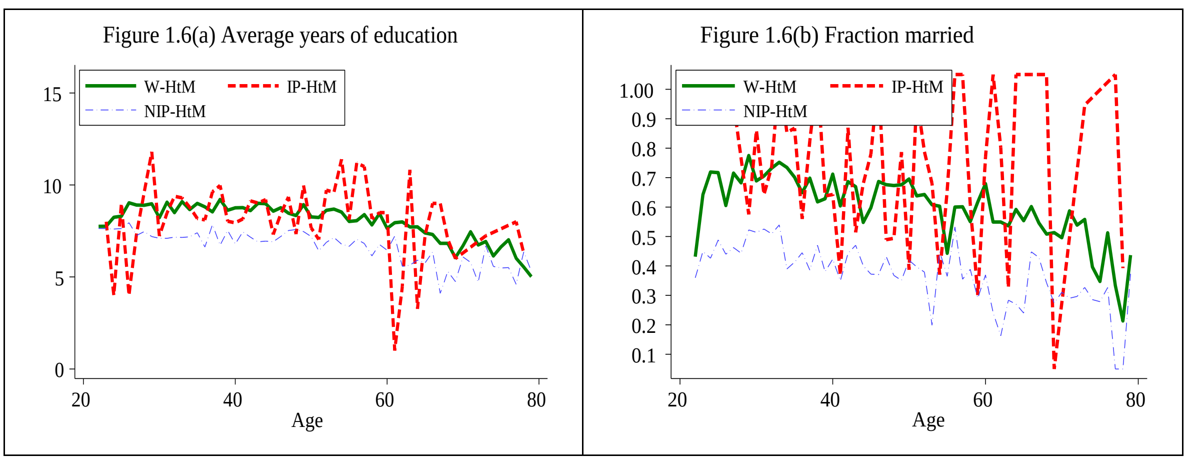


Figure 1.6(c) Average number of children

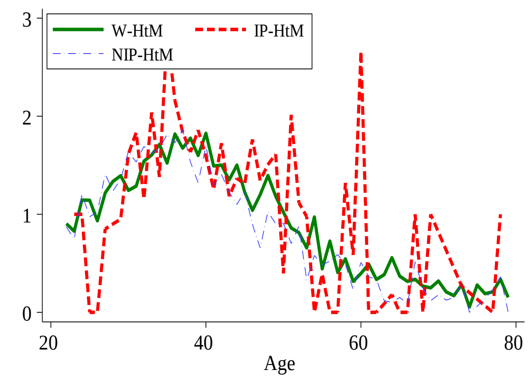


Figure 1.6(d) Median income

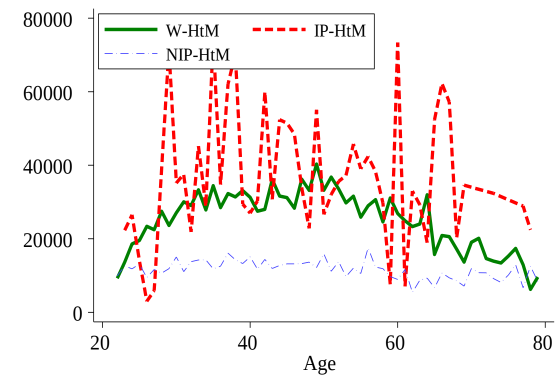


Figure 1.6(e) Fraction with at least one unemployed member

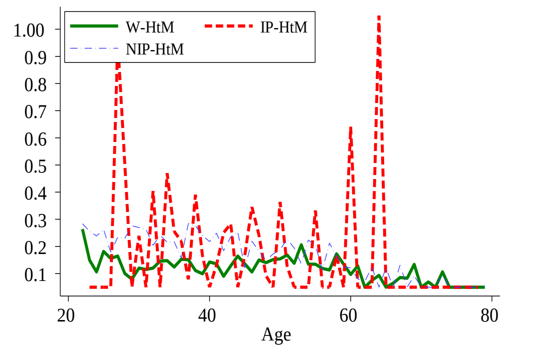


Figure 1.6(f) Fraction of income from government benefits

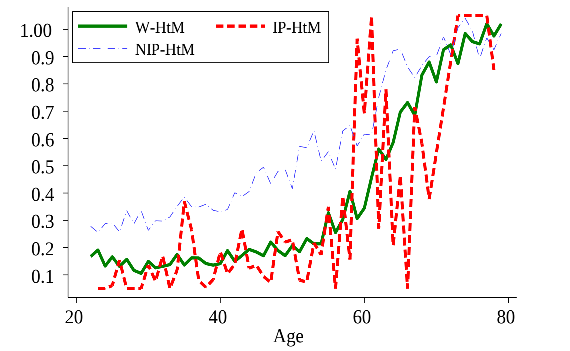
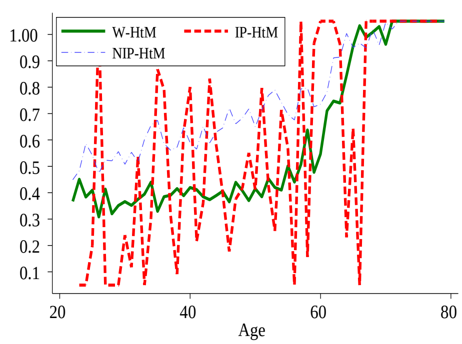
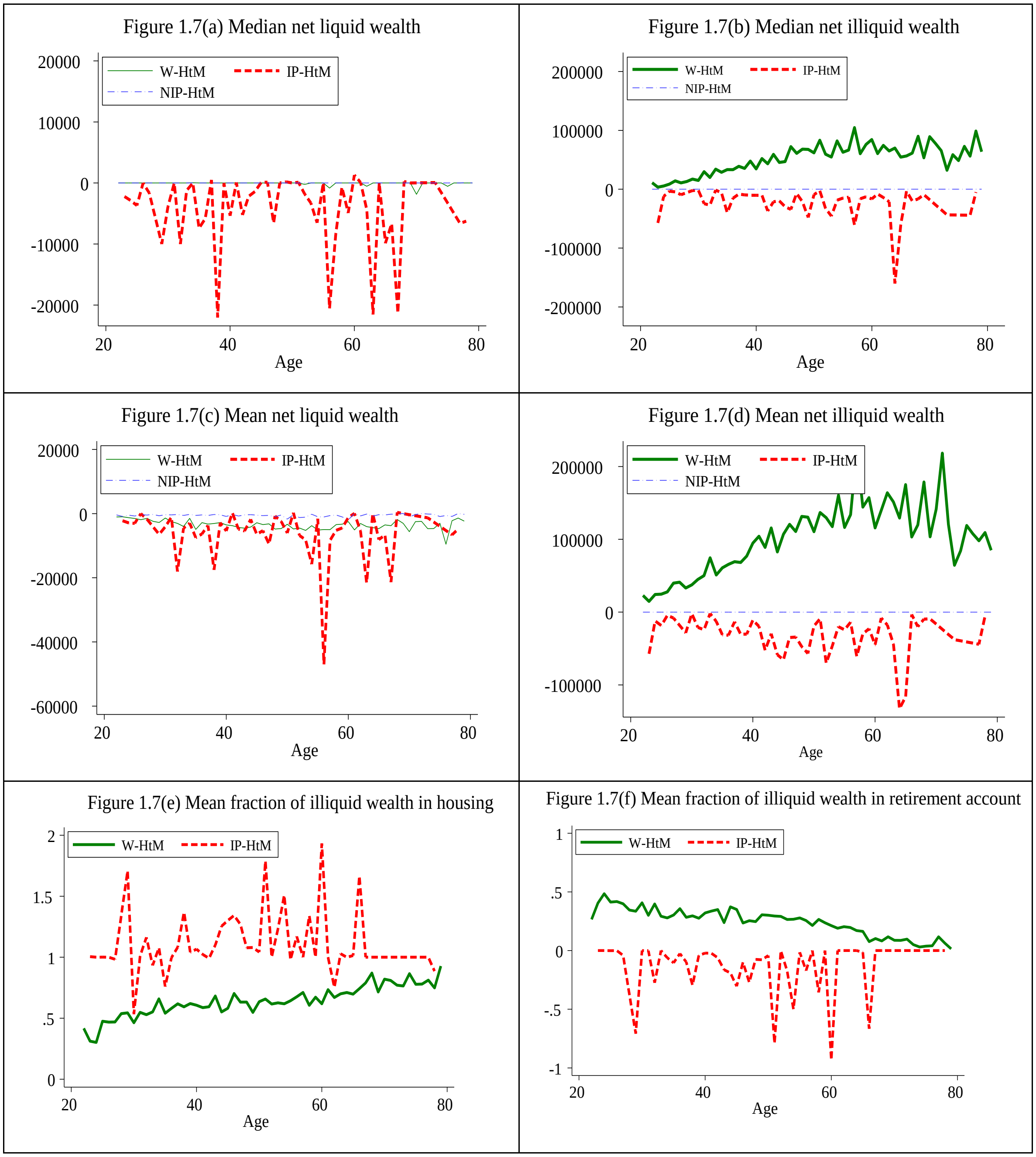


Figure 1.6(g) Fraction of households who receive government benefits



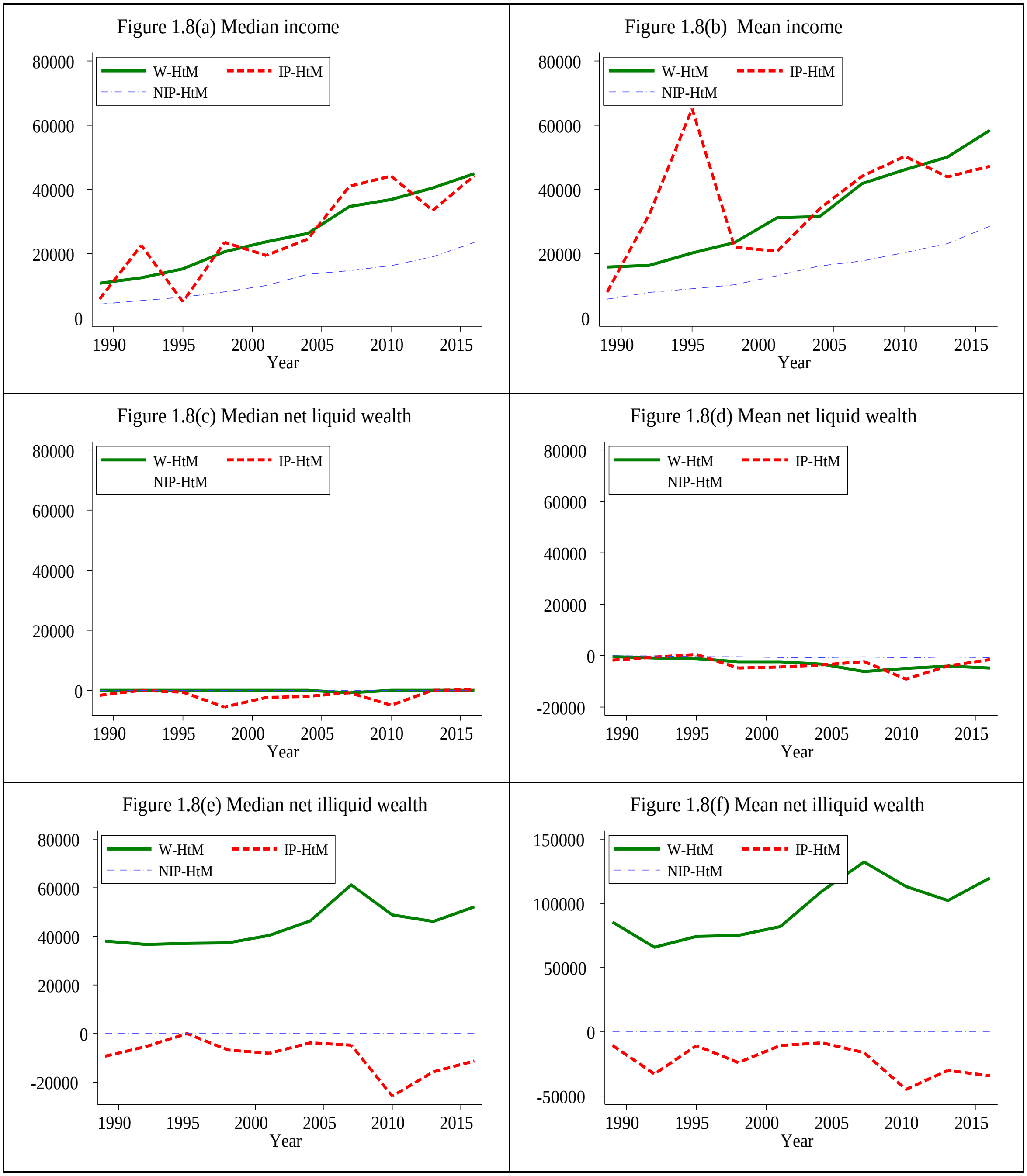
Note: Age refers to that of the head of the household. Average years of education refer to that of the head of the household. Author's calculations based on the pooled 1989–2016, Survey of Consumer Finances (SCF) United States, age limit 22-79. See text for full description of the data.

Figure 1. 7 Age Profile of the Portfolio Composition of the IP-HtM, NIP-HtM, and W-HtM Households



Note: Age refers to that of the head of household. To reduce the sensitivity to outliers, I compute means after trimming the overall top and bottom 0.1 percent of the statistic's distribution. Author's calculations based on the pooled 1989–2016, Survey of Consumer Finances (SCF) United States, age limit 22-79. See text for full description of the data.

Figure 1. 8 Income and Portfolio Composition[5] of different HtM Households over the Years



Note: Author's calculations based on the pooled 1989–2016, Survey of Consumer Finances (SCF) United States, age limit 22-79. See text for full description of the data.

[5] Visit Table A 1.1 and A1.2 in Appendices for more information.

APPENDIX

Table A1. 1 Portfolio Characteristics by HtM Status.

Different HtM Households	WHtM	NHtM	IPHtM	NIPHtM
Liquid wealth / monthly income: mean	-1.243	18.069	-2.108	-0.444
Liquid wealth / monthly income: p10	-3.691	-0.035	-5.291	-0.633
Liquid wealth / monthly income: p25	-1.611	0.601	-2.718	0
Liquid wealth / monthly income: p50	0.001	1.995	-1.23	0
Liquid wealth / monthly income: p75	0.103	7.873	0.069	0.062
Liquid wealth / monthly income: p90	0.187	30.675	0.168	0.147
Housing fraction of illquid wealth: mean	0.595	0.593	1.267	.
Housing fraction of illquid wealth: p10	0	0	1	.
Housing fraction of illquid wealth: p25	0.161	0.29	1	.
Housing fraction of illquid wealth: p50	0.821	0.657	1	.
Housing fraction of illquid wealth: p75	1	0.96	1.261	.
Housing fraction of illquid wealth: p90	1	1	1.68	.
Retirement fraction of illquid wealth: mean	0.331	0.328	-0.29	.
Retirement fraction of illquid wealth: p10	0	0	-0.664	.
Retirement fraction of illquid wealth: p25	0	0	-0.246	.
Retirement fraction of illquid wealth: p50	0.044	0.23	0	.
Retirement fraction of illquid wealth: p75	0.629	0.588	0	.
Retirement fraction of illquid wealth: p90	1	0.993	0	.
Fraction with negative liquid wealth	0.384	0.104	0.574	0.113
Fraction with positive equity in housing	0.786	0.708	0	0
Fraction with positive retirement	0.542	0.613	0.407	0
Fraction with negative illiquid wealth	0	0.027	1	0

Source: Author’s calculations based on the Pooled 1989–2016, Survey of Consumer Finances (SCF) United States, age limit 22-79. See text for full description of the data.

Note: To reduce the sensitivity outliers, means are computed after trimming the overall top and bottom 0.1 percent of that statistic’s distribution.

Table A1. 2 Portfolio Composition of N-HtM Households

	Net Illiquid wealth			Net Liquid wealth		
Waves	Total	Median	Mean	Total	Median	Mean
1999-2015	3444000000	77000	194224	1543000000	13000	87016
1999	286100000	63000	146590	139300000	12000	71337
2001	345300000	73000	171198	177800000	12000	88130
2003	363800000	85500	177827	181300000	14600	89490
2005	499100000	110000	256628	196500000	15000	101043
2007	505100000	120000	256398	205800000	14000	104481
2009	402200000	88250	222975	190800000	15000	105746
2011	376900000	64500	186976	157000000	12000	77859
2013	318100000	56000	157477	154500000	11000	76479
2015	347000000	52000	176930	138200000	11800	70472

Source: Author's calculations based on the United States Panel Study of Income Dynamics (PSID) pooled 1999-2015 waves, age limit 30-57. See text for full description.

CHAPTER 2

CONSUMPTION RESPONSE OF THE INDEBTED HAND-TO-MOUTH HOUSEHOLDS TO TRANSITORY INCOME SHOCKS

2.1 Introduction

This chapter investigates how total consumption and different subcategories of consumption such as food, nonfood, durable and nondurable goods of indebted hand-to-mouth (IP-HtM) households react to a transitory income change. In addition, I describe the responses to the unexpected income shocks for the social sector, healthcare, and utilities, which are different components of nonfood items. I compare these results with other hand-to-mouth households (discussed in Chapter 1), poor hand-to-mouth (P-HtM), not indebted poor hand-to-mouth (NIP-HtM) and wealthy hand-to-mouth (W-HtM).

I collected pooled data from the *Household and Individual Dataset* for the period of 1999-2015 at the Panel Study of Income Dynamics (PSID). I estimate the marginal propensity to consume (MPC) out of transitory income shocks of the IP-HtMs for total consumption and examine the MPCs of food, nonfood, durable and nondurable consumption expenditure of IP-HtM households. In addition, I describe the MPCs for the social sector, healthcare, and utilities, which are different items of the nonfood item category.

A longitudinal data set that includes information on income, consumption, and liquid and illiquid wealth at the household level is necessary to estimate the MPCs. I use the 9 waves of pooled data (1999–2015) from the PSID survey on the United States household portfolios.

Using the methodology proposed by Blundell, Pistaferri, and Preston (2008), Kaplan and Violante (2010), and Kaplan et al. (2014), I estimate the consumption response to transitory changes in income. Unlike these studies, I use the updated sample periods with enriched data, estimate the transmission coefficients of income shocks to consumption for IP-HtM households, and find the MPCs separately for other types of HtM households. These two empirical analyses differentiate this study from Blundell et al. (2008) and Kaplan et al. (2014).

In data, results show that in the baseline specification, MPC of the total consumption for the IP-HtM households is 0.97. However, it is 0.42, 0.23, 0.48, 0.71, and 0.62 for nondurable, durable, nonfood, food, and utilities, respectively. In comparing these results to the responses of P-HtM, NIP-HtM and W-HtM households, I find that the consumption of IP-HtM households is the most responsive (highest MPC) for all consumption items except durables, healthcare, and social sector expenditure in the baseline specification. This suggests that the government can obtain the maximum effectiveness of its stimulatory policies for the IP-HtM households. This study can help government design and execute the fiscal policies directing the highest stimulatory effect during economic slowdown.

The remainder of this paper is organized as follows: section two presents the literature review, section three discusses the data and methodology, section four explores the results and robustness, and the final section concludes.

2.2 Literature Review

Several studies estimate MPC for different groups of households based on their economic stratum. Using panel data on the United States households, Dynan, Skinner, and Zeldes (2004), and McCarthy (1995) found that the MPC is higher for lower income households. Likewise, Jappelli and Pistaferri (2014) using data on Italian households found that the MPC of households with lower cash-on-hand is higher than that of the more affluent households. Using a panel dataset of U.S. households, Filer and Fisher (2007) identified households that are more likely to be credit constrained as those who have filed for bankruptcy in the past 10 years. They found that these households tend to earn lower incomes (before and after bankruptcy filing) and show higher MPCs. Using data from the Household Expenditure Survey (HES), Murugasu, Wei, and Hwa (2013) estimated the MPC out of disposable income for Malaysian households and examined how the propensities differ across income brackets. Their findings show that the MPC from income for poor households is higher when compared with higher income households. The MPCs differ from 0.81 for those earning below Malaysian ringgit 1,000(RM1,000) to 0.25 for those earning above RM10,000.

Hayashi (1985) determined that the reasons poorer households have higher MPCs are that they have credit-constraints, an inability to save and possibly lower levels of financial knowledge. He also noted that credit constraints, or credit rationing, arise when households cannot borrow the amount they desire. Lower income households have less access to credit markets due to their current and expected future lower incomes in addition to lower ownership of usable assets for collateral for loans. When subject to temporary negative income shocks, these households would like to but are unable to borrow against their expected future incomes and consume less than optimal at that point, making it most likely that an increase in income will be consumed rather than saved.

Beverly and Sherraden (1999) considered the hypothesis that financial literacy similarly plays a role in the savings and consumption behavior of households. Their argument is that lower income individuals, who often have a lower level of education, also tend to be less financially literate. Meanwhile, Lawrance (1991) and Bucks and Pence (2008) showed that poorer households tend to have lower foresight when it comes to financial planning. Therefore, lower income households are inclined to be less aware of the available savings instruments and are less likely to surrender consumption to accumulate assets, making consumption more sensitive to income shocks. Moreover, the lower level of financial literacy makes lower income households less likely to buy insurance to help smooth consumption from unanticipated income shocks. Furthermore, Lusardi and Tufano (2015) emphasized that low-income households are less debt literate and often engage in higher cost borrowing transactions.

By focusing on the different categories of HtM households, Kaplan et al. (2014) estimated that the MPC of the W-HtM households is the highest, around 0.30. The point estimate of the MPC for P-HtM is 0.24, and is less than 0.13 for N-HtM.

Knowing the MPC informs policy makers about the effects of fiscal stimulus policies on aggregate consumption. MPC can, however be derived for finer categories of consumption for a more precise targeting of these policies. Johnson, Parker, and Souleles (2006) considered spending on strictly nondurable goods such as food and alcoholic beverages (at and away from home), utilities (and fuels and public services), household operations, public transportation, gas and motor oil, personal care, tobacco, and miscellaneous goods. They broadly defined nondurable goods adding expenditures on apparel goods and services, healthcare expenditures (excluding payments by employers or insurers), and reading materials, following Lusardi (1996), but did not include education. They studied the response of consumption to the 2001 fiscal stimulus implemented in the United States and show that 37 percent of the rebate goes toward increased consumption of nondurable goods and about 11 percent toward increased consumption of food. Kaplan and Violante (2014a) prepared a similar correction and found close results. Misra and Surico (2014) refined the technique to account for heterogeneity in the response of consumption and estimated a marginal propensity to spend on nondurable goods of 0.25.

In his pioneering study, Bodkin (1959) designed an experiment looking at the consumption behavior of World War II veterans after their receipt of unanticipated dividend payments from the National Service Life Insurance. Bodkin considered the dividend payments to be unexpected and that they represented a windfall source of income and derived a point estimate of the MPC nondurables of 0.72. Souleles (1999) exploited tax refunds between 1979 and 1990 and found the MPC for nondurable goods out of a transitory income gain ranged between 0.5 and 0.9 within the quarter following receipt and statistically significant.

Browning and Crossley (2003) estimated that the MPC for nondurable goods was either zero or very small. However, the MPC for durable goods is very large for impatient agents. Paradoxically, it can be large also for the patient agents if the agents are unconstrained. They noted that patient agents without any constraint naturally carry forward debt so that they are less able to maintain purchases of durables in distress.

Parker, Souleles, Johnson, and McClelland (2013) showed the importance of distinguishing between nondurable and total spending and found that households spent between 0.12 and 0.30 of their 2008 United States stimulus payments on nondurable goods; when durable goods are included this rises to between 0.50 and 0.90. These studies adequately estimate the impact of a fiscal stimulus during an economic downturn; nonetheless, because the MPC out of unexpected income gains is usually higher when households are in a low earnings state, they may be overestimating the response of consumption to a typical transitory income shock.

Browning and Crossley (2009) found in their study among Canadian unemployed workers that those with lower unemployment benefits reduced expenditure on durable goods more. Aaronson, Agarwal, and French (2012) showed households experiencing a minimum wage increase augmented expenditure on durables more than on nondurables and the collateralized debts of these households concomitantly rose.

Krueger and Perri (2011), using the Italian Survey of Household Income and Wealth (1987-2008) and the two waves of the PSID (2004-2006) data, estimated that for households that have neither wealth nor real estate nondurable consumption changes by about 23 percent in response to a short run (two years) change in post-tax labor income; whereas, financial wealth responds by about17 percent. They also found that changes in spending on durable goods move in the same direction with income shocks but less so than changes in spending on nondurables.

Christelis, Georgarakos, Jappelli, Pistaferri, and Rooij (2017) derived the average MPC corresponding to nondurable consumption to be in the range of 0.15 to 0.25. They also showed that it rises with age and is larger at low levels of economic resources.

2.3 Data and Methodology

I use longitudinal PSID data to examine the consumption behavior of IP-HtM households. Based on the definitions of different HtMs described in chapter 1, and using the methodology proposed by Blundell et al. (2008), Kaplan and Violante (2010), and Kaplan et al. (2014), I derive the MPC out of transitory income shocks for various HtM households. For most specifications, I derive that the IP-HtM households have the highest MPC out of unexpected change in income.

I use the updated sample period with enriched data to estimate the transmission coefficients of income shocks to total consumption and various items of consumption for IP-HtM households. I also find the MPCs separately for other types of HtM households. These two empirical analyses make this study unique from Blundell et al. (2008) and Kaplan et al. (2014).

2.3.1 Data Source, Sample Selection and Definitions

It is necessary to have a longitudinal data set with information on income, consumption, and liquid and illiquid wealth at the household level to estimate the consumption response to income shocks for IP-HtM households with different groups of HtM households. I use 9 waves of pooled data (1999–2015) from the PSID.

I start with the PSID core sample and drop the households with missing values on race of head, or region where head grew up, education of head. Also eliminated are households whose income fall by more than 80 percent, or are below $100, grow more than 500 percent, and top-coded income or consumption. Since the identification of the coefficients of interest requires a minimum of three periods, I only keep the households that appear in the sample in at least three consecutive waves. I keep the households where the head is 30-57 years old. The final sample has 50,475 observations over the pooled 9 sample years.

I follow Blundell, Pistaferri, and Saporta-Eksten (2016), and Kaplan et al. (2014) to construct the consumption measure. Table 2.1 displays the definitions of consumption; various items of consumption such as nondurable, durable, food and noon food; income; liquid assets; liquid debts; and net illiquid wealth. Net liquid asset is liquid assets minus liquid debts.

2.3.2 Methodology

I use the methodology of Kaplan et al. (2014) to estimate the consumption response to transitory changes in income. A more detailed description of this methodology is available in Blundell et al. (2008) and Kaplan and Violante (2010) I mention only the important steps here:

(i) Regressing log income and log consumption expenditures on year and cohort dummies, education, race, family structure, employment, geographic variables, and interactions of year dummies with education, race, employment, and region.

(ii) Constructing the first-differenced residuals of log consumption Δc_{it} and log income Δy_{it}.

(iii) A period is 2 years as the survey is biannual. The income process y_{it} is an error component model that consists of orthogonal permanent and i.i.d.

(independently and identically distributed) components. Therefore, income growth is represented by

$\Delta y_{it} = \alpha_{it} + \Delta\theta_{it}$

where θ_{it} is the transitory shock and α_{it} is the permanent shock.

(iv) The MPC, the Blundell et al. (2008) estimator of the transmission coefficient of transitory income shocks to consumption is

$$\widetilde{MPC}_t = \frac{cov\ (\Delta c_{it,}\, \Delta y_{i,t+1})}{cov\ (\Delta y_{it,}\, \Delta y_{i,t+1})}$$

(v) The exact MPC out of a transitory shock is expressed as

$$MPC_t = \frac{cov\ (\ \Delta c_{it,}\, \theta_{it}\ )}{var(\theta_{it}\ )}$$

(vi) The estimator in (iv) is a consistent estimator of (v) if the household has no foresight of future shocks, explicitly:

$$cov\left(\Delta c_{it,}\, \alpha_{i,t+1}\right) = cov\left(\ \Delta c_{it,}\, \theta_{i,t+1}\ \right) = 0,$$

(vii) The estimator is realized by an instrumental (IV) regression of Δc_{it} on Δy_{it}, instrumented by $\Delta y_{i,t+1}$. It is mentioned that $\Delta y_{i,t+1}$ is correlated with the transitory shock (θ_{it}) at *t*, but not with the permanent one (α_{it}).

Kaplan and Violante (2010) indicate the presence of tight borrowing constraints does not bias the estimate of the transmission coefficient for transitory shocks.

2.4 Results and Robustness

Table 2.2 provides the results for total consumption. The MPC of the IP-HtM households is the highest, around 0.97 in the baseline specification. The point estimate of the MPC for the P-HtM is 0.39, for the NIP-HtM 0.34, and for the W-HtM 0.37. This result is not surprising if one thinks of the IP-HtM as W-HtM facing temporary severe financial constraints. There are two intuitions behind the responsiveness behavior of IP-HtM. First, the IP-HtM households spend the maximum share of their income on mortgage payments leaving a small portion for consumption. This results in high responsiveness in their consumption behavior due to any positive income shock. Second, IP-HtM households face credit constraints that induce them to spend most of their share of increased transitory income for consumption.

The rest of the rows in Table 2.2 show robustness tests with respect to the definition of household composition, income and consumption, and the assumed pay period (monthly income). The MPCs of the IP-HtM group are always the highest among all other HtM households as in the baseline specification. Under the definition of "monthly pay period," the MPC decreases for IP-HtM and W-HtM households, whereas it increases for P-HtM and NIP-HtM households. If the definition is either "male household head" or "pretax earnings" or "include food stamps," the MPCs fall for all types of HtM households. On the contrary, if the marital status of the head is stable, it increases for all groups of HtM except W-HtM. Table 2.2 also reports that MPCs decrease for P-HtM, NIP-HtM, and W-HtM if the sample is restricted to the households of the continuously married.

The important outcome that the consumption of the IP-HtM shows the highest sensitivity to temporary income shocks out of all HtM households is similar to the findings of some recent studies. Baker (2013) incorporated several original sources of household data on income, consumption expenditures, and household financial statements to examine the co-movement of consumption and income at the micro level during the Great Recession. He shows that expenditures of highly indebted households with illiquid assets are especially sensitive to income fluctuations. Cloyne and Surico (2014) executed a long span of expenditure survey data for the United Kingdom and a narrative measure of exogenous income tax changes. They also showed that the homeowners with high leverage ratios present large and persistent consumption responses to tax shocks. Misra and Surico (2014) built on the study of Johnson et al. (2006) and Parker et al. (2013) on the 2001 and 2008 fiscal stimulus payment programs in the United States. They found that for both stimulus episodes the largest propensity to consume out of the tax rebate is among households that own real estate but have high levels of mortgage debt.

Tables 2.3 and 2.4 show the MPC of nondurable consumption is higher than that of the durable for all groups of HtM households except W-HtM in the baseline specification. This finding is supported by Krueger and Perri (2011). For nondurable consumption, the MPC of the IP-HtM households is the highest, around 0.42, among other HtMs. On the other hand, W-HtM households are the most responsive for durable consumption with the MPC of about 0.49.

Table 2.3 reveals that for the first three robustness tests the MPC of nondurable drops for all groups of HtMs. In contrast to that, MPC increases for all if the pay period is monthly instead of biweekly. Table 2.3 also shows that for households with stable marital status, MPC of IP-HtM and W-HtM show the same pattern of change. However, MPC changes in the opposite direction for these two groups if the household head is male. Table 2.4 displays that only the MPCs of W-HtM households are statistically significant for durable consumption.

Table 2.5 summarizes the results for nonfood consumption. The point estimate of the MPC for the IP-HtM is the highest, around 0.48 and for the W-HtM is the lowest, 0.27 in the baseline specification. The remaining rows in Table 2.5 offer a robustness analysis and show that IP-HtM households are the most responsive out of all HtMs for all alternative definitions.

Table 2.5 reports that for the first two robustness tests the MPC of nonfood decreases for all groups of HtMs. On the other hand, MPC rises for all HtMs if the pay period under consideration is monthly. I also observe in Table 2.5 that for households with a stable marital status, MPC of IP-HtM and W-HtM changes in the same direction. However, I see the opposite pattern of change of MPCs for these two groups if the household head is male and the households are continuously married.

Table 2.6 explores the finding that the IP-HtM households are more responsive in the food expenditure to sudden changes in income than other groups of HtMs in the baseline specification.

The remaining rows in Table 2.6 offer a robustness analysis with respect to the definition of income and consumption, household composition, and the assumed pay period. I find statistically significant results only for IP-HtM and W-HtM households. The ranking of MPC among the two HtMs is always as in the baseline specification. Table 2.6 also shows that the MPC of IP-HtM declines for all alternative definitions. Like IP-HtM, I see the same pattern of change of MPC for W-HtM with the only exception being if I consider a monthly pay period.

Table 2.7 displays that IP-HtM households are the most responsive, around 0.62, and NIP-HtM households are the least responsive, around 0.21, in utility expenditure to the transitory income shocks in the baseline. In robustness tests, only in the definitions of "pre-tax earnings" and "include food stamps" does MPC change in the same direction for IP-HtM and W-HtM. However, I see the opposite pattern of change of MPC of these two groups for all other definitions in robustness tests.

Tables 2.8 and 2.9 show that the MPCs of healthcare and social sector (education and healthcare together) consumption are statistically significant for all HtM households except IP-HtM. P-HtM, NIP-HtM, and W-HtM households that experience income rises tend to seek better education and healthcare (social sector consumption) and to send their children to better educational institutions. For the first three alternative definitions and "households with male head," the MPCs of healthcare expenditure drop for all HtM households except IP-HtM. Under the monthly pay period system, the MPCs of P-HtM and NIP-HtM increase, whereas it decreases for W-HtM.

2.5 Conclusion

The study is a detailed analysis of how the total consumption and the different subcategories of consumption such as food, nonfood, durable, nondurable, social sector, utilities, and healthcare of the IP-HtM households react to the transitory income changes. This study also compares these results to other HtM households.

Findings show that the MPC of the total consumption for IP-HtM is the highest among all the categories of households in the baseline specification. The study also shows that among all HtMs, the consumption of IP-HtM households is the most responsive for all consumption items except durables, healthcare, and social sector expenditure in the baseline specification. These results are also supported by some recent studies. Cloyne and Surico (2014) performed a long span of expenditure survey data for the United Kingdom and a narrative measure of exogenous income tax variations. They also found that the homeowners with high leverage ratios show large and persistent consumption responses to tax changes. Misra and Surico (2014) built on the study of Johnson et al. (2006) and Parker et al. (2013) on the 2001 and 2008 fiscal stimulus payment programs in the United States. They showed that for both stimulus episodes the largest responses to consumption out of the tax rebate is among households that own real estate but have high levels of mortgage debt. Baker (2013) combined several original sources of household data on consumption expenditures, income, and household financial statements to examine the co-movement of consumption and income at the micro level during the Great Recession. He finds that expenditures of highly indebted households with illiquid assets are especially sensitive to income variations. Results suggest that the stimulatory government's policies have maximum effectiveness for the IP-HtM households. This study can encourage governments to design and implement their fiscal policies by aiming for the highest stimulatory effect during an economic downturn.

TABLES

Table 2. 1 Definitions of Consumption, Income, Liquid Assets, Liquid Debts and Net Illiquid Wealth (PSID)

Items	Components
Consumption	Utilities, public transportation, food, childcare, healthcare, gasoline, car maintenance, and education.
Nondurable	Food, utilities, public transportation, and healthcare.
Durable	Cars (vehicle loan payment and down payment), housing (mortgage payments), and home improvement (household furnishing and equipment).
Nonfood	Utilities, public transportation, childcare, healthcare, gasoline, car maintenance, and education.
Food	Food at home and away from home.
Social sector	Education and healthcare.
Income	Government transfers plus labor earnings of a household.
Liquid assets	Money market funds, value of checking and savings accounts, certificates of deposit, savings bonds, and treasury bills, together with directly held shares of stock in publicly held corporations, investment trusts or mutual funds.
Liquid debts	Value of debts such as student loans, medical or legal bills, credit cards, and personal loans.
Net illiquid wealth	Summation of the value of private annuities or IRAs, value of home equity, net value of other real estate, value of other investments in trusts or estates, bond funds, and life insurance policies.

Table 2. 2 Marginal Propensity to Consume out of Transitory Income Shocks for Different Types of HtM Households (total consumption) [a]

	P-HtM	IP-HtM	NIP-HtM	W-HtM
Baseline	0.391*** (0.089)	0.974*** (0.366)	0.344*** (0.092)	0.371*** (0.080)
Pre-tax earnings[b]	0.210*** (0.056)	0.861*** (0.283)	0.166*** (0.057)	0.215*** (0.060)
Include food stamps[c]	0.380*** (0.087)	0.941*** (0.363)	0.335*** (0.090)	0.350*** (0.080)
Continuously married households[d]	0.280 (0.251)	1.401** (0.678)	0.082 (0.276)	0.160 (0.126)
Stable marital status[e]	0.467*** (0.116)	1.110*** (0.364)	0.399*** (0.123)	0.333*** (0.089)
Households with male heads[f]	0.220* (0.113)	0.632 (0.429)	0.186 (0.117)	0.252*** (0.095)
Monthly income[g]	0.430*** (0.084)	0.958*** (0.287)	0.378*** (0.088)	0.350*** (0.073)

Source: Author's calculations based on the United States Panel Study of Income Dynamics (PSID) 1999-2015 waves, age limit 30-57. See text for full description.

a. Boot-strapped standard errors based on 250 replications in parentheses. Standard errors are in parentheses. ***p < 0.01. **p < 0.05. *p < 0.10.

b. Gross income before taxes are paid. Transfers are excluded.

c. Food stamps are included among transfers.

d. Restricted to continuously married households.

e. Restricted to households with no change in marital status.

f. Households with female heads (mostly single) are excluded.

g. Pay period is set to one month instead of two weeks.

Table 2. 3 Marginal Propensity to Consume out of Transitory Income Shocks for Different Types of HtM Households (nondurable)[a]

	P-HtM	IP-HtM	NIP-HtM	W-HtM
Baseline	0.230*** (0.060)	0.422** (0.194)	0.217*** (0.064)	0.254*** (0.046)
Pre-tax earnings[b]	0.104*** (0.036)	0.410*** (0.152)	0.089** (0.038)	0.157*** (0.035)
Include food stamps[c]	0.215*** (0.057)	0.376* (0.192)	0.204*** (0.060)	0.226*** (0.046)
Continuously married households[d]	0.214 (0.156)	0.415 (0.320)	0.177 (0.178)	0.185** (0.077)
Stable marital status[e]	0.253*** (0.080)	0.295 (0.186)	0.249*** (0.088)	0.232*** (0.0530
Households with male heads[f]	0.185*** (0.072)	0.540** (0.241)	0.157** (0.077)	0.174*** (0.055)
Monthly income[g]	0.272*** (0.056)	0.482*** (0.157)	0.256*** (0.060)	0.277*** (0.042)

Source: Author's calculations based on the United States Panel Study of Income Dynamics (PSID) 1999-2015 waves, age limit 30-57. See text for full description.

a. Boot-strapped standard errors based on 250 replications in parentheses. Standard errors are in parentheses. ***p < 0.01. **p < 0.05. *p < 0.10.

b. Gross income before taxes are paid. Transfers are excluded.

c. Food stamps are included among transfers.

d. Restricted to continuously married households.

e. Restricted to households with no change in marital status.

f. Households with female heads (mostly single) are excluded.

g. Pay period is set to one month instead of two weeks.

Table 2. 4 Marginal Propensity to Consume out of Transitory Income Shocks for Different Types of HtM Households (durable)[a]

	P-HtM	IP-HtM	NIP-HtM	W-HtM
Baseline	0.197 (0.475)	0.235 (0.605)	0.141 (0.576)	0.488*** (0.190)
Pre-tax earnings[b]	0.205 (0.269)	0.452 (0.465)	0.102 (0.313)	0.281** (0.131)
Include food stamps[c]	0.240 (0.362)	0.082 (0.601)	0.229 (0.416)	0.410** (0.185)
Continuously married households[d]	0.704 (1.009)	1.899 (0.990)	0.012 (1.470)	0.191 (0.264)
Stable marital status[e]	0.598 (0.585)	0.652 (0.548)	0.582 (0.763)	0.319 (0.196)
Households with male heads[f]	-0.003 (0.552)	0.298 (0.728)	-0.166 (0.679)	0.513** (0.224)
Monthly income[g]	0.202 (0.439)	0.437 (0.469)	0.064 (0.553)	0.516*** (0.174)

Source: Author's calculations based on the United States Panel Study of Income Dynamics (PSID) 1999-2015 waves, age limit 30-57. See text for full description.

a. Boot-strapped standard errors based on 250 replications in parentheses. Standard errors are in parentheses. ***p < 0.01. **p < 0.05. *p < 0.10.

b. Gross income before taxes are paid. Transfers are excluded.

c. Food stamps are included among transfers.

d. Restricted to continuously married households.

e. Restricted to households with no change in marital status.

f. Households with female heads (mostly single) are excluded.

g. Pay period is set to one month instead of two weeks.

Table 2. 5 Marginal Propensity to Consume out of Transitory Income Shocks for Different Types of HtM Households (nonfood)[a]

	P-HtM	IP-HtM	NIP-HtM	W-HtM
Baseline	0.297*** (0.076)	0.483** (0.224)	0.285*** (0.081)	0.275*** (0.054)
Pre-tax earnings[b]	0.126*** (0.047)	0.450** (0.177)	0.112** (0.050)	0.144*** (0.040)
Include food stamps[c]	0.261*** (0.074)	0.426* (0.224)	0.251*** (0.079)	0.232*** (0.053)
Continuously married households[d]	0.308** (0.182)	0.555 (0.371)	0.261 (0.206)	0.172* (0.090)
Stable marital status[e]	0.350*** (0.103)	0.299 (0.213)	0.355*** (0.113)	0.220*** (0.060)
Households with male heads[f]	0.223** (0.090)	0.684** (0.282)	0.188* (0.097)	0.183*** (0.064)
Monthly income[g]	0.338*** (0.070)	0.586*** (0.184)	0.319*** (0.076)	0.294*** (0.049)

Source: Author's calculations based on the United States Panel Study of Income Dynamics (PSID) 1999-2015 waves, age limit 30-57. See text for full description.

a. Boot-strapped standard errors based on 250 replications in parentheses. Standard errors are in parentheses. ***p < 0.01. **p < 0.05. *p < 0.10.

b. Gross income before taxes are paid. Transfers are excluded.

c. Food stamps are included among transfers.

d. Restricted to continuously married households.

e. Restricted to households with no change in marital status.

f. Households with female heads (mostly single) are excluded.

g. Pay period is set to one month instead of two weeks.

Table 2. 6 Marginal Propensity to Consume out of Transitory Income Shocks for Different Types of HtM Households (food)[a]

	P-HtM	IP-HtM	NIP-HtM	W-HtM
Baseline	0.063 (0.094)	0.710** (0.311)	0.013 (0.010)	0.189*** (0.070)
Pre-tax earnings[b]	0.018 (0.058)	0.654*** (0.235)	-0.020 (0.061)	0.170*** (0.051)
Include food stamps[c]	-0.053 (0.071)	0.378 (0.306)	-0.084 (0.074)	0.130** (0.063)
Continuously married households[d]	-0.281 (0.238)	0.283 (0.463)	-0.402 (0.277)	0.167 (0.109)
Stable marital status[e]	0.027 (0.124)	0.627** (0.303)	-0.040 (0.137)	0.182** (0.081)
Households with male heads[f]	-0.005 (0.112)	0.548 (0.355)	-0.053 (0.121)	0.117 (0.081)
Monthly income[g]	0.110 (0.085)	0.700** (0.275)	0.058 (0.091)	0.231*** (0.063)

Source: Author's calculations based on the United States Panel Study of Income Dynamics (PSID) 1999-2015 waves, age limit 30-57. See text for full description.

a. Boot-strapped standard errors based on 250 replications in parentheses. Standard errors are in parentheses. ***p < 0.01. **p < 0.05. *p < 0.10.

b. Gross income before taxes are paid. Transfers are excluded.

c. Food stamps are included among transfers.

d. Restricted to continuously married households.

e. Restricted to households with no change in marital status.

f. Households with female heads (mostly single) are excluded.

g. Pay period is set to one month instead of two weeks.

Table 2. 7 Marginal Propensity to Consume out of Transitory Income Shocks for Different Types of HtM Households (utilities)[a]

	P-HtM	IP-HtM	NIP-HtM	W-HtM
Baseline	0.242**	0.622**	0.208**	0.212***
	(0.098)	(0.285)	(0.106)	(0.060)
Pre-tax earnings[b]	0.121**	0.473**	0.099	0.109**
	(0.059)	(0.216)	(0.063)	(0.044)
Include food stamps[c]	0.216**	0.472*	0.195*	0.136**
	(0.094)	(0.285)	(0.100)	(0.061)
Continuously married households[d]	-0.093	0.387	-0.193	0.215**
	(0.210)	(0.477)	(0.240)	(0.097)
Stable marital status[e]	0.262	0.632**	0.217	0.164**
	(0.126)	(0.293)	(0.140)	(0.068)
Households with male heads[f]	0.161	0.639*	0.114	0.187***
	(0.122)	(0.350)	(0.132)	(0.069)
Monthly income[g]	0.254***	0.587**	0.219**	0.245***
	(0.090)	(0.225)	(0.098)	(0.056)

Source: Author's calculations based on the United States Panel Study of Income Dynamics (PSID) 1999-2015 waves, age limit 30-57. See text for full description.

a. Boot-strapped standard errors based on 250 replications in parentheses. Standard errors are in parentheses. ***p < 0.01. **p < 0.05. *p < 0.10.

b. Gross income before taxes are paid. Transfers are excluded.

c. Food stamps are included among transfers.

d. Restricted to continuously married households.

e. Restricted to households with no change in marital status.

f. Households with female heads (mostly single) are excluded.

g. Pay period is set to one month instead of two weeks.

Table 2. 8 Marginal Propensity to Consume out of Transitory Income Shocks for Different Types of HtM Households (healthcare)[a]

	P-HtM	IP-HtM	NIP-HtM	W-HtM
Baseline	0.749***	0.003	0.812***	0.587***
	(0.246)	(0.843)	(0.261)	(0.176)
Pre-tax earnings[b]	0.509***	0.248	0.522***	0.528***
	(0.168)	(0.759)	(0.176)	(0.147)
Include food stamps[c]	0.479**	-0.330	0.540**	0.496***
	(0.232)	(0.869)	(0.244)	(0.174)
Continuously married households[d]	0.170	-0.665	0.281	0.085
	(0.491)	(1.675)	(0.516)	(0.277)
Stable marital status[e]	0.507*	-0.359	0.597*	0.640***
	(0.230)	(0.809)	(0.325)	(0.203)
Households with male heads[f]	0.733**	-0.053	0.797***	0.258
	(0.291)	(1.105)	(0.306)	(0.203)
Monthly income[g]	0.7634***	0.064	0.833***	0.566***
	(0.233)	(0.688)	(0.250)	(0.158)

Source: Author's calculations based on the United States Panel Study of Income Dynamics (PSID) 1999-2015 waves, age limit 30-57. See text for full description.

a. Boot-strapped standard errors based on 250 replications in parentheses. Standard errors are in parentheses. ***p < 0.01. **p < 0.05. *p < 0.10.

b. Gross income before taxes are paid. Transfers are excluded.

c. Food stamps are included among transfers.

d. Restricted to continuously married households.

e. Restricted to households with no change in marital status.

f. Households with female heads (mostly single) are excluded.

g. Pay period is set to one month instead of two weeks.

Table 2. 9 Marginal Propensity to Consume out of Transitory Income Shocks for Different Types of HtM Households (social sector: healthcare and education) [a]

	P-HtM	IP-HtM	NIP-HtM	W-HtM
Baseline	0.612*** (0.166)	-0.133 (0.516)	0.669*** (0.177)	0.469*** (0.114)
Pre-tax earnings[b]	0.317*** (0.106)	-0.007 (0.394)	0.332*** (0.112)	0.269*** (0.084)
Include food stamps[c]	0.433*** (0.156)	-0.103 (0.473)	0.472*** (0.167)	0.302*** (0.111)
Continuously married households[d]	0.409 (0.344)	-0.313 (0.844)	0.557 (0.380)	0.407** (0.186)
Stable marital status[e]	0.456** (0.216)	-0.225 (0.533)	0.530** (0.236)	0.432*** (0.130)
Households with male heads[f]	0.652*** (0.196)	-0.085 (0.560)	0.717*** (0.211)	0.293** (0.132)
Monthly income[g]	0.714*** (0.155)	0.079 (0.415)	0.771*** (0.1680	0.489*** (0.102)

Source: Author's calculations based on the United States Panel Study of Income Dynamics (PSID) 1999-2015 waves, age limit 30-57. See text for full description.

a. Boot-strapped standard errors based on 250 replications in parentheses. Standard errors are in parentheses. ***p < 0.01. **p < 0.05. *p < 0.10.

b. Gross income before taxes are paid. Transfers are excluded.

c. Food stamps are included among transfers.

d. Restricted to continuously married households.

e. Restricted to households with no change in marital status.

f. Households with female heads (mostly single) are excluded.

g. Pay period is set to one month instead of two weeks.

CHAPTER 3

DETERMINANTS OF HEALTHCARE EXPENDITURE OF A RESOURCE-CONSTRAINED COMMUNITY: EVIDENCE FROM RICKSHAW PULLERS

3.1 Introduction

Ill health adversely affects the standard of living, especially of the working class of a society, by reducing real income. The pathways from ill health to poverty work through the direct costs of treatment and non-medical care and the indirect costs of lost income (due to days absent from work and reduced productivity) of the affected person. The working-class population-for instance, daily laborers-become more efficient and their working hours increase if they have good health. They go to work almost every day and do a painstaking job. The health status of this population is affected by poverty, lack of education and awareness, lack of available affordable and high-quality healthcare, and negligence among policymakers. Auvinen (1997) showed that a well-planned healthcare financing system protects a population against the financial risks of ill health. Aghion, Caroli, and Garcia-Penalosa (1999) and Baer, Campino, and Cavalcanti (2001) presented that households' out-of-pocket (OOP) healthcare expenditure is a major component of health system finance in middle- and low-income countries. Bardhan (1997) showed that when households face substantial medical expenses, they are pushed into poverty or forced deeper into poverty.

Low-income households like those of day laborers live from hand to mouth, and they spend a large proportion of their income on their basic survival necessities. They cannot afford their required healthcare services. They might decrease their healthcare expenditure if there is any increase in OOP medical costs, and even small copayments might reduce the likelihood of receiving necessary healthcare. Healthcare providers can give better services to the working-class population if they know the determinants of healthcare expenditure among this group of people. The purpose of this study is to estimate the determinants of healthcare expenditure in a resource-constrained population. This study focuses on a survey conducted among rickshaw pullers (RPs) in Dhaka, Bangladesh. RPs are representative of a resource-constrained community in a developing country, since they have underprivileged social and economic status due to the nature of the service they provide to their society, they have insufficient access to high-quality healthcare services, and they lack human and physical capital. A survey of rickshaw pullers conducted by Begum and Sen (2004) revealed that rickshaw driving on a regular basis is extremely hard work, and about 85 percent of sampled respondents had left their jobs due to their inability to continue such arduous work. They also found that about 75 percent of current and 90 percent of former drivers mentioned “physical exhaustion” and “fatigue” when discussing rickshaw pulling.

According to the *New Encyclopaedia Britannica* (1993), “rickshaw” originated from the Japanese word *Jinrikisha*, which literally means “human-powered vehicle”. During the 1860s, rickshaws were first made in Japan (Saito, 1979). Rajvanshi (2002) explained that rickshaws were used as a means of transportation for the social elite; however, they still play an important role in the transportation system, particularly in third-world countries. Hakim and Rahman (2016); Kamruzzaman and Hakim (2015); and Hakim and Talukder (2016) showed that RPs are among the most disadvantaged segments of the population.

Rickshaw is one of the most important means of transportation in Bangladesh. Almost all the RPs in Dhaka come from the rural areas of Bangladesh, since they do not get work in the villages. Though driving a rickshaw is a hard job, their income is inadequate to support their families. They don't get proper medical treatment. Though a rickshaw is a non-motorized and environmentally friendly means of transportation, continuous driving for many years takes a huge toll on RPs' physical ability (Begum & Sen, 2005).

Bangladesh is one of the poorest countries in the world, with a per capita gross domestic product (GDP) of US$747.34 in 2012 (World Health Organization, 2013). The per capita income of the RP community was $260.12 in 2013 (Table 3.1), which falls well below the threshold of $693.50 in a year, which is defined as extreme poverty (World Bank, 2016).[6] Per capita total health expenditure in Bangladesh was US$67 in 2011 (World Health Organization, 2011) and $14.84 in 2013 for the RP community (Table 3.1). As one of the lower-middle–income countries, and with a population of 160 million (Bangladesh Bureau of Statistics, 2016; July 2014 estimate), Bangladesh has been struggling to improve its population's health for long time. On average, households in Bangladesh spend 11 percent of their total household budget on health (Rahman, Gilmour, Saito, Sultana, & Shibuya, 2013), whereas households in the RP community spend about 5.7 percent (Table 3.1).

In their study on RPs in rural Bangladesh, Islam, Hakim, Safeuzzaman, Hague, and Alam (2016) showed that 72 percent of respondents earned about $4–5 and only 6

[6] The World Bank (2016) defines "extreme poverty" as living on less than $1.90 per person per day. Based on this information, the per capita annual income of an extremely poor person is below $693.50 (= $1.90*365).

percent earned about $6 on a daily basis. They also found that 22 percent of respondents were underweight, about 28 percent had a cough and cold, 18 percent had diarrhea, and 10 percent had asthma and gastric ulcers.

In my survey of RPs, respondents were asked about various aspects of healthcare received over the last year and about illness and demographic information of household members, such as age and years of schooling of the household head, family size, duration of the illness episode, distance of the residence from the healthcare facility/hospital, etc. Using this survey, the paper employs a flexible Box-Cox model regression method to find the determinants of healthcare expenditure for a resource-constrained community. The results suggest that households' annual income, distance of residence from healthcare center/hospital, age of the household head, duration of illness episode, years of schooling, family size, and marital status affect healthcare expenditure. The income elasticity of healthcare expenditure of about 0.55 implies that healthcare is a necessary good. This study is unique in its analysis of the determinants of healthcare expenditure of the working-class population, using cross-sectional microdata. The specific research questions are:

i. What are the impacts of duration of illness episode in the households of a resource-constrained community on their healthcare spending?

ii. Which individual household determinants, such as annual income, distance, education, family size, and marital status, best explain household healthcare expenditure?

iii. Does the age of the household head play any role in the household's healthcare spending in a resource-limited community?

The remainder of this chapter is organized as follows: Section 2 presents the literature review; section 3 discusses the methodology of the study, which explores the sources of data and the methods followed; section 4 portrays the descriptive analysis for the core sample; section 5 analyzes the results; and section 6 puts forward conclusions.

3.2 Literature Review

Wagstaff and Doorslaer (2000) portrayed that the healthcare OOP expenditure of most low- and middle-income Asian countries was regressive, as social assistance and fee exemptions were either non-existent or, where they existed, were not well targeted at those who were most in need. Using household survey data from 11 Asian countries, Van Doorslaer et al. (2006) showed that OOP payments are the key source of healthcare financing, and the ratio of OOP payments to total household healthcare expenditure is between 30 and 82 percent. They also found that the overall prevalence of absolute poverty in 11 Southeast Asian countries is 14 percent higher than conventional estimates of poverty that do not consider OOP payments for healthcare. In addition, they portrayed that Vietnam, India, China, and Bangladesh depend to a great degree on OOP healthcare spending, so experiencing an extensive catastrophic payment leads directly to poverty.

Su, Pokhrel, Gbangou, and Flessa (2006) presented that demographic characteristics and severity of illness play an important role in healthcare expenditure.

Akanda and Minowa (2011) underlined the importance of analyses of demand for healthcare and healthcare expenditure at the household level for effective health policy formulation. They argued that efficient community- and country-bound health policy cannot be designed without adequate information on household healthcare expenditure, especially for middle- and low-income countries.

Andersen (2016) showed that the presence of illness is the most obvious factor that determines households' OOP healthcare spending, while need is a perceived phenomenon. Barros (1998); Di Matteo and Di Matteo (1998); Roberts (2000); Karatzas (2000); Giannoni and Hitiris (2002); Clemente, Marcuiello, Montanes, and Pueyo (2004); Herwartz and Theilen (2003); Koening et al. (2003); Di Matteo (2005); Crivelli, Filippini, and Mosca (2006); Mosca (2007); You and Kobayashi (2011); Foster (2016); and Molla, Chi, and Mondaca (2017) used income as one of the most important determinants of healthcare expenditure.

There is little agreement regarding the value of the income elasticity of demand for healthcare services. Getzen (2000) showed that this elasticity varies according to the level of analysis (individual, regional, or aggregate) of the research.

Newhouse (1977); Leu (1986); Brown (1987); Parkin, McGuire, and Yule (1987); and Gerdtham, Sogaard, Andersson, and Jonsson (1992) found that healthcare expenditure in the Organization for Economic Cooperation and Development (OECD) countries at the aggregate level before 1998 obtained values for income elasticity greater than 1. Roberts (2000); Rous and Hotchkiss (2003); and Clemente et al. (2004) also determined an income elasticity greater than unity. But Di Matteo and Di Matteo (1998); Barros (1998); Karatzas (2000); Giannoni and Hitiris (2002); Koening et al. (2003); Herwartz and Theilen (2003); Okunade (2005); Di Matteo (2005); and Molla et al. (2017) identified an income elasticity with values between 0 and 1.

Di Matteo and Di Matteo (1998); Karatzas (2000); Roberts (2000); Giannoni and Hitiris (2002); Di Matteo (2005); Crivelli et al. (2006); You and Kobayashi (2011); Molla et al. (2017); and Mahumud et al. (2017) found that people spend more on healthcare with increasing age.

Gertler and Gaag (1990) showed that income, prices, and travel time are the main determinants of healthcare expenditure. You and Kobayashi (2011) also identified that healthcare expenditure increases with chronic disease and residence in urban areas.

Jochmann (2004) treated the number of doctor visits in the last 3 months as the dependent variable, whereas the independent variables consisted of socioeconomic characteristics and variables that described the health condition of the individual. They included a self-perceived health satisfaction index, degree of handicap in percentage points, relationship status, age, education, as well as variables measuring disability. They found that the number of doctor visits increases with age until the age of 85 and decreases thereafter.

Some studies have been conducted in developing countries using cross-sectional data to identify determinants of healthcare expenditure.

Sodani (1999) considered "healthcare expenditure" as the dependent variable in his paper on the tribal households of three selected districts of Rajasthan, India. The explanatory variables were "duration of illness episode," "number of visits to source of care," and "distance of source of care from the residence of households". Howlader, Routh, Hossain, Saha, and Khuda (2000) found that the amount of healthcare expenditure varies with change in income, type of disease, and type of provider and estimated the elasticities of demand for healthcare using cross-sectional data that were collected using a structured questionnaire administered to rural household heads in Bangladesh in 1997. Rous and Hotchkiss (2003) used the Nepal Living Standards Survey, a nationally representative sample of households from 1996, to investigate the determinants of household OOP health expenditures. Okunade (2005) presented econometric model findings of the determinants of per-capita health expenditure (at PPP) for 26 African countries using 1995 cross-sectional data. They found that economic and other determinants - per-capita GDP (at PPP), ODA (US$), Gini income inequality index, population dependency ratio, internal conflicts, and the percentage of births attended by trained medical workers - capture 74 percent of the variations in health expenditures. Hague and Barman (2010) used household data from Chittagong Division to research the factors of healthcare expenditure and showed that income has a significant effect on people's choice of healthcare provider and on their amount of healthcare spending. Chang and Hague (2014) showed that illness, educational level, type of medical consultants, household characteristics, location, and wealth significantly affect the level of healthcare spending. Mahumud et al. (2017) and Molla et al. (2017) estimated the predictors of health expenditure among Bangladeshi households using the Bangladesh Household Income and Expenditure Survey (BHIES) 2010. Mahumud et al. (2017) used age, marital status, education level, wealth quintile, sex, and first symptoms of illness as the predictors of healthcare expenditure. Molla et al. (2017) presented that household healthcare expenditure is determined by income, presence of health shock, presence of chronic illness, proportion of illiterate members in the family, household durable goods, family size, proportion of female members, and rural residence.

The studies conducted in these countries have some limitations. These studies mainly either used national data or were conducted in pocket areas that do not represent any specific community (like the working-class population). Moreover, to show a causal relationship, a limited number of studies have used modern econometric techniques of analysis. Specification is essential for the formulation of a health system financing policy for a community. This study uses cross-sectional microdata on resource-constrained households like RPs in Dhaka collected via a survey conducted in 2014.

Sufficient knowledge about the extent, determinants, and elasticities of healthcare expenditure is necessary to devise strategies to increase the allocative efficiency of resources, ensure the proper utilization of the existing resources, and improve the quality of services. Analysis of healthcare expenditure is also decisive in designing strategies aimed at achieving financial sustainability for a program. The findings of the study will be helpful in designing and executing a healthcare financing policy for households in a working-class community.

3.3 Data and Methodology

3.3.1 Data

The study is based on a sample of 120 RPs. At the time of the survey, all of them were living and working in Dhaka. A stratified sample was drawn at random from different points of the city,[7] ensuring the inclusion of all age groups. Selected RPs were interviewed using a more detailed structure. Respondents were asked about healthcare expenditures and various aspects of healthcare received in 2013 by all the RPs'

[7] City points covered are Khilgoan (Mouchak, Modhubug, Malibug), Lalbug (Puran Dhaka, BDR 1 No. Gate, Beribad), Mohammadpur (Adabor, Gigatola), Jattrabari, Mirpur, and Dhanmondi areas.

household members. Data were collected from RP households who could choose from public and private providers. They usually went to low- and medium-quality registered private providers. Data on household annual income were also collected. Some information on other costs involved in receiving healthcare were available, but not in the required form. Though data on travel cost were available, data on travel time and waiting time were not available. Data on age of the RP, years of schooling, marital status, and distance of residence from the healthcare center and the duration of their household members' illness episodes were collected. RPs were the main or only earning member of their households. RPs were also the household heads.

3.3.2 Empirical Regression Model Specification

Most of the studies on determinants of OOP healthcare expenditure in developing countries have used ordinary least square (OLS) methods as econometric techniques. Malik and Syed (2012) used the Household Integrated Economic Survey (HIES) and the Pakistan Standard of Living Measurement (PSLM) Survey for the years 2004–05 to find socioeconomic determinants of household OOP payments for healthcare in Pakistan. Vasudeva and Okunade (2009) applied OLS and robust least absolute error (LAE) estimation methods to estimate the core determinants of health expenditure using data from 44 African countries for the year 2001. Molla et al. (2017) and Mahumud et al. (2017) also applied OLS to estimate the predictors of health expenditure among Bangladeshi households using the Bangladesh Household Income and Expenditure Survey (BHIES) 2010. Mosca (2007) formulated a log-log in which he estimated the total healthcare expenditure per capita (THE) by OLS with a sample of 20 countries in the

OECD for which sufficient information was available from 1990–2000. Hague and Barman (2010) attempted to find out the determinants of household healthcare expenditure using a multi-equation recursive estimation procedure. First, they used a binary logit model to estimate the probability of being ill, which was then used as an independent variable in the second stage logit model for provider choice. Ordinary least squares (OLS) estimates were obtained for the parameters of the healthcare expenditure model in the third stage. Mugisha, Kouyata, Gbangou, and Sauerborn (2002) used a Tobit model to examine OOP expenditure on healthcare in Nouna, Burkina Faso. However, Rous and Hotchkiss (2003) recommended that a Tobit model should be applied carefully in the case of health expenditure. They developed a full information maximum likelihood model to control the endogeneity of sickness and provider choice using data from Nepal. Hjortsberg (2003) used data from Zambia and validated the method to control endogeneity bias by generating a selection term as a regressor in OLS estimation of healthcare expenditure for corresponding providers.

I am going to use a Box-Cox transformation model (Box & Cox, 1964) to identify the determinants of healthcare expenditure for a resource-constrained community using cross-sectional microdata. The Box-Cox transformation model has been applied in various economic applications. Examples include price changes (Millon, Gressel, & Mulkey, 1984), demand and supply elasticities (Bessler et al., 1984), money demand (Boylan & O’Muircheartaigh, 1981; Mills, 1978; Spitzer, 1976; White, 1972; Zarembka, 1968), hedonic price models (Blackley, Follain, & Ondrich, 1984; Megbolugbe, 1986), exports (Davison, Arnade, & Hallahan, 1989; Miner, 1982), and import demand (Blaylock & Smallwood, 1985; Boylan, Cuddy, & O’Muircheartaigh, 1980, 1982;

Hwang, 1981; Khan & Ross, 1977); other examples include Granger and Newbold (1976), Hopwood, McKeown, and Newbold (1984), Smyth and Dua (1986), Guerrero (1987), and Montmarquette and Blais (1987).

Box-Cox transformation models are useful for minimizing functional form bias, since the commonly assumed linear and log-log forms in expenditure models are nested in the generalized flexible power family of the transformation model. Gerdtham, Sogaard, Jonsson, and Andersson (1991) used this method in their OECD health expenditure model, choosing the quadratic square root transformation as the best. Okunade (1985) earlier tested a different set of functional forms - linear, linear-log, log-linear, and log-log for selecting the best-fitting model for the 1960–72 data of each African country. Gbesemete and Gerdtham (1992) selected a log-log model based on the RESET model selection criterion rather than the Box-Cox power tests using 1984 data from Africa. Okunade (2005) showed the results of the determinants of per-capita health expenditure for 26 African countries using 1995 cross-sectional data and flexible Box-Cox model regression methods.

The multiple regression model, specifying values of the dependent variable h to depend on values of a set of regressors m, takes the general form

$$h = f(\mathrm{m}, \gamma) \tag{3.1}$$

where the data column vector h_i ($i = 1, 2, \ldots, k$) ∈ matrix m (with a column of 1s for the intercept), each m_i is orthogonal to the other m_i s (data columns of the regressors making up the design matrix), and the model residuals ε are normally distributed with 0 means and a finite variance σ^2. The regression parameter estimates of γ_i ($\in$ vector γ) captures the slope $\frac{\partial h}{\partial m_i}$.

Health expenditure data are typically not normally distributed (Tuckman, Chang, & Okunade, 1999), and cross-sectional data model residuals are usually not homoscedastic. Consequently, as in Carroll and Ruppert (1988), healthcare expenditure data in this study can be optimally modeled by either assuming that h (skewed response data) is capable of transformation to symmetry using the generalized flexible Box-Cox power family of data transformations model or by specifying ε, the density of the model residuals, as belonging to a class of skewed densities. The first method produces maximum likelihood estimates (MLEs) of the regression model gradients (γ in equation (3.1)) conditional on standard deviation (σ) and scalar power estimates (λ) that are generally consistent with the observed dataset. On the other hand, the second approach is a generalized linear model (GLM). I discuss the first estimation method here.

The generalized flexible, or fully flexible, fairly parametrically rich Box-Cox transformation model (BCTM) is as follows in case of our healthcare expenditure analysis:

$$h^{\lambda} = \frac{h^{\lambda-1}}{\lambda} \tag{3.2}$$

where h is the total healthcare expenditure and λ is a scalar parameter that is jointly estimated with other parameters of the regression model. The transformation could make the residuals more closely normal and less heteroskedastic (Box & Cox, 1964). The transform embeds several functional forms (Cook & Weisberg, 1982) admitting transformation of strictly positive data values for a continuous variable h, which takes the form

$$h^{(\lambda)} = \begin{cases} h - 1 & \text{if } \lambda = 1 \\ \ln(h) & \text{if } \lambda = 0 \\ 1 - \frac{1}{h} & \text{if } \lambda = -1 \end{cases} \qquad (3.3)$$

The power family of the transformation model, also skew-correcting for the dependent variable h, will be applied to the left- and right-hand-side variables (excluding the dummy variable), to permit different λ power transformations of each variable in the healthcare expenditure model. I can fit the following Box-Cox models for our healthcare expenditure study and obtain the maximum likelihood estimates of the parameters for different models (Drukker, 2000).

Theta model

$$h_j^{(\theta)} = \gamma_0 + \gamma_1 m^{(\lambda)}{}_{1j} + \gamma_2 m^{(\lambda)}{}_{2j} + \ldots + \gamma_k m^{(\lambda)}{}_{kj} + \alpha_1 n_{1j} + \alpha_2 n_{2j} + \ldots + \alpha_l n_{lj} + \varepsilon_j \qquad (3.4)$$

where $\varepsilon \sim N(0, \sigma^2)$. Here, the dependent variable, h, is subject to a Box-Cox transformation with the parameter θ. Each of the independent variables, $m_1, m_2, \ldots, m_k$, is transformed by a Box-Cox transform with parameter λ. The independent variables (e.g., dummy variables), $n_1, n_2, \ldots, n_l$, are not transformed.

Lambda model

$$h_j^{(\lambda)} = \gamma_0 + \gamma_1 m^{(\lambda)}{}_{1j} + \gamma_2 m^{(\lambda)}{}_{2j} + \ldots + \gamma_k m^{(\lambda)}{}_{kj} + \alpha_1 n_{1j} + \alpha_2 n_{2j} + \ldots + \alpha_l n_{lj} + \varepsilon_j \qquad (3.5)$$

where $\varepsilon \sim N(0, \sigma^2)$. Here, the dependent variable, h, and each of the independent variables, $m_1, m_2, \ldots, m_k$, are transformed by a Box-Cox transformation with the common parameter λ. The independent variables (e.g., dummy variables), $n_1, n_2, \ldots, n_l$, are not transformed.

Left-hand-side–only model

$$h_j^{(\lambda)} = \gamma_0 + \gamma_1 m_{1j} + \gamma_2 m_{2j} + \ldots + \gamma_k m_{kj} + \varepsilon_j \quad (3.6)$$

where $\varepsilon \sim N(0, \sigma^2)$. Here, the dependent variable, h, is subject to a Box-Cox transformation with the parameter λ.

Right-hand-side–only model

$$h_j = \gamma_0 + \gamma_1 m^{(\lambda)}_{1j} + \gamma_2 m^{(\lambda)}_{2j} + \ldots + \gamma_k m^{(\lambda)}_{kj} + \alpha_1 n_{1j} + \alpha_2 n_{2j} + \ldots + \alpha_l n_{lj} + \varepsilon_j \quad (3.7)$$

where $\varepsilon \sim N(0, \sigma^2)$. Each of the independent variables, $m_1, m_2, \ldots, m_k$, is transformed by a Box-Cox transformation with parameter λ. The independent variables (e.g., dummy variables), $n_1, n_2, \ldots, n_l$, are not transformed.

Estimation of likelihood function for different models

In the internal computations,

$$h^\lambda = \frac{h^{\lambda - 1}}{\lambda} \text{ for all } \lambda > 0$$

$$\ln(h) \text{ otherwise}$$

The unconcentrated log likelihood for the theta model is

$$\ln L = \left(-\frac{I}{2}\right) \ln\{(2\pi) + \ln(\sigma^2)\} + (\theta - 1)\sum_{i=1}^{I} \ln(hi) - \left(\frac{1}{2\sigma^2}\right) \text{SSR}$$

where SSR = sum of squared residuals

$$= \sum_{i=1}^{I} \left(h^{(\theta)} - \gamma_0 + \gamma_1 m_{i1}^{(\lambda)} + \gamma_2 m_{i2}^{(\lambda)} + \cdots + \gamma_k m_{jk}^{(\lambda)} + \alpha_1 n_{i1} + \gamma\alpha_2 n_{i2} + \cdots + \alpha_l n_{jl}\right)^2$$

Writing the SSR in matrix form,

$$\text{SSR} = (h^{(\theta)} - M^{(\lambda)}d' - Nq')'(h^{(\theta)} - M^{(\lambda)}d' - Nq')$$

where $h^{(\theta)}$ is an I × 1 vector of elementwise transformed data, $M^{(\lambda)}$ is an I × k matrix of elementwise transformed data, N is an I × l matrix of untransformed data, d is a 1 × k vector of coefficients, and q is a 1 × l vector of coefficients.

Let

$Z_\lambda = (M^{(\lambda)} \;\; N)$

be the horizontal concatenation of $M^{(\lambda)}$ and N and

$$v' = \begin{pmatrix} d' \\ q' \end{pmatrix}$$

be the vertical concatenation of the coefficients' yields

$SSR = (h^{(\theta)} - Z_\lambda v')' (h^{(\theta)} - Z_\lambda v')$

For given values of λ and θ, the solutions for v′ and σ^2 are

$v^{*\prime} = (Z'_\lambda Z_\lambda)^{-1} Z'_\lambda h^{(\theta)}$

and

$\sigma^{*2} = (\frac{I}{2}) (h^{(\theta)} - Z_\lambda v^{*\prime})' (h^{(\theta)} - Z_\lambda v^{*\prime})$

Substituting these solutions into the log-likelihood function yields the concentrated log-likelihood function:

$\ln L_c = (-\frac{I}{2}) \ln \{ (2\pi) + 1 + \ln(\sigma *^2)\} + (\theta - 1) \sum_{i=1}^{I} \ln(hi)$

Similar calculations yield the concentrated log-likelihood function for the lambda model:

$\ln L_c = (-\frac{I}{2}) \ln \{ (2\pi) + 1 + \ln(\sigma *^2)\} + (\lambda - 1) \sum_{i=1}^{I} \ln(hi)$

For the left-hand-side–only model:

$\ln L_c = (-\frac{I}{2}) \ln \{ (2\pi) + 1 + \ln(\sigma *^2)\} + (\theta - 1) \sum_{i=1}^{I} \ln(hi)$

For the right-side–only model:

$\ln L_c = (-\frac{I}{2}) \ln \{ (2\pi) + 1 + \ln(\sigma *^2)\}$

where σ^{*2} is specific to each model and is defined analogously to that in the theta model.

The chi-square (χ^2) likelihood ratio test statistic, applied to the log-likelihood function values of the BCTM versus each of the restricted regression models, is used to guide selection of the optimal functional form from among the parametrically more restrictive competing models (linear-linear, linear-log, log-linear, log-log) that are nested in my more general BCTM specification. The research goal of the BCTM model is to fit the appropriate functional form model to the observed data in order to reduce the specification bias that could arise from the fitting the a priori restrictive functional form models.

The expected relationship of each determinant to healthcare expenditure (*HCEX*) in a BCTM regression model estimation of the type $h^{(\lambda 0)} = m^{(\lambda 1)}\gamma + \varepsilon$, where γ is the slope vector, h is *HCEX*, m is matrix of independent variables, and ε is the residual vector, is as follows:

$$(\text{HCEX})^{(\lambda)} = \gamma_0 + \gamma_1 (\text{LINC})^{(\lambda 1)} + \gamma_2 (\text{DIST})^{(\lambda 2)} + \gamma_3 (\text{AGE})^{(\lambda 3)} + \gamma_4 (\text{DOIE})^{(\lambda 4)}$$

$$+ \gamma_5 (\text{FS})^{(\lambda 5)} + \gamma_6 (\text{YSHH})^{(\lambda 6)} + \alpha_1 (\text{MSHH}) + \varepsilon \qquad (3.8)$$

where, in accordance with a priori theoretical expectations,

$\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6, \alpha_1 > 0$.

The dependent variable:

HCEX = healthcare expenditure of household

Explanatory variables:

LINC = annual income (last-year income)

DIST = distance of residence from healthcare center/hospital

AGE = age of household head

DOIE = duration of illness episode

FS = family size

YSHH = years of schooling of household head

Dummy variable:

MSHH = marital status of household head, MSHH = 1 if married; MSHH = 0 if unmarried

3.4 Descriptive Statistics

Table 3.1 shows that the mean age of household head (RP) was about 36 years. The average number of years of schooling was about 3 years. Most of the sample RPs were married (85 percent). Only about 22 percent of RPs owned their rickshaws, and the rest of the RPs rented their rickshaws on a daily basis. The average number of family members in an RP household was about 5. The number of income earners in each household was about 2. The average annual income of RP households was $1,227 (BDT 95,406). An RP held $1,826 (BDT 141,968) in wealth on an average. The mean savings of an RP household was $54 (BDT 4,228). Average debt was $63 (BDT 4,892). The average net savings was $-5.50 (BDT -664). The average RP household was sick 47 days in the last year. The mean number of days the household members stayed in the hospital was 5, and they were absent from work about 24 days in the last year. They lost about $158 (BDT 122.79) in the last year due to illness. About 87 percent of RP households receive modern healthcare (registered physician and modern medical facilities). The mean number of visits to the health center was about 7. The average distance from the healthcare center was 2.63 kilometers. The user fee per visit was $0.90 (BDT 70). The travel cost per visit was $0.38 (BDT 30). Medicine cost per visit was $5 (BDT 397). About 74 percent of RP households were satisfied with the quality of healthcare, and 65 percent of the RP households were pleased with the health service they received from the healthcare center. About 84 percent of them were willing to pay for healthcare when they became ill. About 85 percent of them took addictive substances, on which they spent about $0.30 (BDT 23) each day. Average expenditure for total healthcare in an RP household was $70 (BDT 5,408). The per capita total expenditure for healthcare last year was $14.84 (BDT 1146). The share of household budget spent on healthcare was 5.70 percent. Please visit the appendix (Tables A 3.1–A 3.8) for the distribution of different variables.

3.5 Results

I discussed four different Box-Cox models in section 3. Table 3.2 presents a Box-Cox model estimates based on prior studies (Bessler et al., 1984; Blackley et al., 1984; Blaylock & Smallwood, 1985; Boylan & O'Muircheartaigh, 1981; Boylan et al., 1980, 1982; Davison et al., 1989; Gerdtham et al., 1991; Granger & Newbold, 1976; Guerrero, 1987; Hopwood et al., 1984; Hwang, 1981; Khan & Ross, 1977; Megbolugbe, 1986; Millon et al., 1984; Mills, 1978; Miner, 1982; Montmarquette & Blais, 1987; Okunade, 2005; Smyth & Dua, 1986; Spitzer, 1976; White, 1972; Zarembka, 1968). I used the lambda model in my analysis to explain the determinants of healthcare expenditure of a resource-constrained community. Regression estimates used OOP healthcare expenditure as the dependent variable. The p-values are in parentheses.

Results of the lambda model are presented in Column I of Table 3.2. I found the signs of the coefficients as expected except age of the household head. The coefficients of annual income and age of the household head are significant at the 10 percent level.

The duration of illness episode is significant at the 1 percent level, and the distance of the residence from the healthcare center/hospital is significant at the 11 percent level.

The income elasticity of healthcare is 0.547 and significant, implying that healthcare is a normal and necessary good for the resource-constrained community of rickshaw pullers. It shows that a 10 percent increase in income level leads to a 5.4 percent increase in household healthcare expenditure. This result is supported by Di Matteo and Di Matteo (1998); Barros (1998); Karatzas (2000); Giannoni and Hitiris (2002); Koening et al. (2003); Herwartz and Theilen (2003); Okunade (2005); Di Matteo (2005); and Molla et al. (2017). They found income elasticity for healthcare, with values between 0 and 1. Rickshaw pulling is a laborious occupation that requires physical fitness. If RPs become sick, they do not have any other means of earning. This gives rickshaw pullers the motivation to visit doctors when sick.

The coefficient of the distance of the household's residence from the healthcare center/hospital shows that a 10 percent increase in distance leads to a 7.6 percent increase in household healthcare expenditure. Sodani (1999) also showed that "distance of source of care from" can explain the healthcare expenditure increase in the rural and urban areas of three districts of Rajasthan, India.

The age coefficient shows that healthcare expenditure is inversely associated with age, and a 10 percent increase in an RP's age leads to a 24.5 percent decrease in household healthcare expenditure. This is supported by Begum and Sen (2004). They explained that driving a rickshaw on a regular basis is hard work, and after the age of 50, it is difficult to drive throughout the entire week, so drivers tended to drive 3 to 4 days a week, which may cause a decrease in their daily income. This drop in income causes a decrease in their healthcare expenditure, since the number of dependents in a household increases as the head grows older, requiring him to redistribute his healthcare expenditure toward food and other consumption items. However, Di Matteo and Di Matteo (1998); Karatzas (2000); Roberts (2000); Giannoni and Hitiris (2002); Di Matteo (2005); Crivelli et al. (2006); You and Kobayashi (2011); Molla et al. (2017); and Mahumud et al. (2017) observed that people spent more on healthcare with increasing age. This implies that the healthcare expenditure is inversely associated with age of the household head in a resource-constrained community and positively associated for others.

The coefficient of duration of illness episode shows that OOP healthcare expenditure is positively associated with the number of sick days of the household members, and a 10 percent increase in duration of illness leads to a 12.6 percent increase in expenditure on health. Sodani (1999) also found a similar direction of the coefficient.

The coefficient of years of schooling of the household head implies that a household head with a greater number of schooling years spends more on healthcare for his household than a household head with fewer schooling years, holding all other variables constant. The RPs with less education either chose alternative or home remedies or were not as well informed about the accessibility of healthcare. Jochmann and Leon-Gonzalez (2004); Hague and Barman (2010); Chang and Hague (2014); Mahumud et al. (2017); and Molla et al. (2017) also observed a similar direction of the coefficient. Moreover, the RPs were born and raised in poor families and must start earning from their childhood or help parents in their household activities instead of going to school. The RPs had on average fewer than 3 years of schooling (Table 3.1). Therefore, level of education affected their healthcare expenditure, but not significantly. However, these findings have been checked with other regression equations and observed to be in the same direction of the coefficient.

Like Molla et al. (2017), I also find that there is a positive association between healthcare expenditure and the size of a family. The result shows that a 10 percent increase in number of family members leads to a 13.6 percent increase in household healthcare expenditure.

The result shows that households with married household heads (RPs) spent more on healthcare than households with unmarried RPs, holding all other variables unchanged. Mahumud et al. (2017) supports this finding.

The robustness results of the lambda model are presented in Table 3.3. Column VII of Table 3.3 shows that a 10 percent increase in number of the dependent family members leads to an 11.5 percent decrease in healthcare expenditure. Okunade (2005) observed the same direction of the coefficient for the variable dependency ratio in his study. All the coefficients of the equations in Table 3.3 show the same direction of the coefficient as in the previous study. Income, distance, age of the household head, and duration of illness episode variables are significant in all the regression equations.

To compare the lambda model with other versions of the Box-Cox model, I report the left-hand-side–only model and right-hand-side–only model in brief. I do not report the other version of the Box-Cox model, the theta model.[8] The results of the left-hand-side–only model and right-hand-side–only model are presented in Table 3.2. Column II presents the results of the left-hand-side–only model. The result shows that healthcare expenditure is inversely associated with the marital status of the household head. But

[8] The theta model did not converge to have definite estimates.

based on the prior study, I expected that healthcare expenditure would be positively related to marital status. The value of the income coefficient is too small to explain. No other coefficient is significant in this model. Column III shows the results of right-hand-side–only model. I expected healthcare expenditure to have a positive association with years of schooling. However, the result shows that they are inversely associated. Though the coefficient of the age of household and the duration of illness episode are significant, other explanatory variables are not statistically significant. The robustness tests of the left-hand-side–only model and right-hand-side–only model are presented in Tables 3.4 and 3.5, respectively.

3.6 Summary, Conclusions, and Implications

This study examined a Box-Cox econometric model of the determinants of health expenditure in a resource-constrained community using cross-sectional microdata on rickshaw pullers, who represent the working-class population.

The results of the study show that annual household income, distance of residence from a healthcare center/hospital, age of the household head, duration of illness episode, years of schooling, family size, and marital status are the main factors of total healthcare expenditure among resource-constrained households. I found that healthcare expenditure is positively associated with household income level, distance of residence from healthcare center/hospital, duration of illness episode, years of schooling of the household head, family size, and marital status, as expected; these associations are supported by previous studies. However, healthcare expenditure is inversely associated with age of the household head; this association in case of a resource-constrained community is opposite of the existing literature.

The income elasticity of about 0.55 signals the tendency for healthcare to behave like a normal and necessary good. Since healthcare is a necessity in the "basic needs" theory of economic development, the way healthcare expenditure in a resource-constrained community responds to changes in income level and other factors is particularly relevant to development policy. Working-class populations in developing countries have unmet healthcare needs, and effective policies and programs are needed to ensure that healthcare services are received in a timely manner.

The distance of a household's residence from the healthcare center/hospital and the duration of an illness episode also play significant roles in determining healthcare expenditure. The results show that a 10 percent increase in the distance leads to a 7.6 percent increase in household healthcare expenditure, and a 10 percent increase in duration of illness leads to a 12.6 percent increase in expenditure on health. Moreover, a 10 percent increase in the number of family members leads to a 13.6 percent increase in household healthcare expenditure.

The finding shows that healthcare expenditure is inversely associated with the age of the household head. It may happen in a resource-constrained community because the earning ability (income level) of day laborers decreases as their age increases. The situation is aggravated when the household head has an accident or experiences severe sickness. Moreover, the number of dependents in the household increases as the head becomes older, requiring redistribution of healthcare expenses toward food and other consumption items.

This study can help policymakers design extensive and effective financial protection mechanisms for the resource-constrained community by finding the predictors of healthcare expenditure. Though the current study shows that healthcare is a necessary good, OOP payments are not an equitable or efficient financing mechanism. Resource-constrained, hardworking poor citizens do not receive the high-quality healthcare services they need, and their standard of living is less than that of other city dwellers. Extensive safety net programs need to be designed and implemented for resource-constrained communities. The quality of healthcare received by this group of households and its availability should be ensured. Precise policy and management improvements in pursuit of better quality and more equitable distribution of resources in the health sector must be undertaken to provide health services to this group of population. Universal healthcare coverage for this group of households should be guaranteed. Governments of different countries need to reinforce existing healthcare programs, and additionally, they should introduce effective new types of safety net for the working-class population in old age, especially if the households have no other earning member. Policymakers can spread their family planning/birth control services more effectively to the doors of such communities to keep the family size small. A specialized bank for the resource-constrained community can be introduced to provide small and medium enterprise loans with low interest rates and insurance policies to cover the loss of injury (Bose, 2014). As per Molla et al. (2017), alternative revenue generation and allocation of resources to cover the health needs of resource-constrained households need to be revisited. For instance, exempting this group of households from fees could reduce their OOP healthcare expenditure and financial burden. This study advocates that countries need to reform their health system financing structures so that the resource-constrained community can meet their unmet healthcare needs.

In future research, the sample size might be increased to derive the healthcare expenditure function for a larger population. The survey could not be conducted widely because of some limitations (e.g., financial and time constraints). On occasion, the respondents did not assist adequately. Moreover, conducting interviews involved several safety concerns during evening hours when RPs were available at home. There is a scope to conduct extensive research by increasing the sample size of the RPs covering the whole of Bangladesh and other countries so that effective policy measures may be taken to improve the health status of a marginalized, poor segment of society. In addition, future research on health spending among the working-class population might consider other resource-constrained communities with different occupations.

TABLES

Table 3. 1 Descriptive Statistics for Core Sample.

Variable	Mean (BDT)	USD($)[9]	N
Age of RP	36.358 (11.349)		120
Years of schooling of RP	2.967 (2.719)		120
Marital status	0.850 (0.358)		120
Ownership of rickshaw	0.217 (0.413)		120
Number of family members of RP	4.717 (1.557)		120
Number of income earners in RP's household	1.717 (0.842)		120
Household annual income	95,406.5 (43,974.67)	1,227	120
Per capita income (household annual income/ average number of family members of RP)	20,226.10	260.12	120
Household wealth	141,968.3 (388745.9)	1,826	120
Household savings	4,228.042 (11100.14)	54	120
Household debt	4,891.667 (10148.31)	63	120
Household net savings	-663.625 (14769.63)	- 5.5	120
Household sick days last year	46.792 (89.194)		120
Number of days stayed in hospital	4.908 (13.074)		120
Number of days absent from work due to illness	23.858 (38.375)		120
Income lost due to last year illness	12,279.5 (51,008.7)	158	120
Received modern healthcare	0.867 (0.341)		120

Note: Standard deviations indicated in parentheses.

[9] Considering the exchange rate $1 = BDT 77.75 as of December 30, 2013, available on the website of Bangladesh Bank (2013), Central Bank of Bangladesh, https://www.bb.org.bd/econdata/exchangerate.php. BDT is the code for the Bangladeshi currency, the Taka.

Table 3.1 Continued

Variable	Mean (BDT)	USD($)[10]	N
Number of visits to healthcare center last year	7.025 (9.585)		120
Distance from healthcare center/hospital(km)	2.630 (3.948)		120
User fee per visit	69.842 (90.555)	0.90	120
Travel cost per visit	29.892 (41.796)	0.38	120
Medicine cost per visit	396.667 (861.474)	5	120
Quality of healthcare if satisfactory	0.742 (0.440)		120
Quality of health service if satisfactory	0.650 (0.479)		120
Willingness to pay for healthcare	0.842 (0.366)		120
Whether any family member takes addictive substances	0.85 (0.358)		120
Money spent on addiction per day	22.925 (21.127)	0.30	120
Total expenditure for healthcare last year	5,407.842 (24787.59)	70	120
Per capita total expenditure for healthcare last year* (total expenditure for healthcare last year/ average number of family members of RP)	1,146.46	14.84	120
Share of household budget spent on healthcare (total expenditure for healthcare last year /household annual income)		5.70 %	120

Note: Standard deviations indicated in parentheses. *The World Bank (2016) defines "extreme poverty" as living on less than $1.90 per person per day. Based on this information, the annual income of an extremely poor person is less than $693.50 (= $1.90*365), so a rickshaw puller's household falls into this category.

[10] Considering the exchange rate $1 = BDT 77.75 as of December 30, 2013, available on the website of Bangladesh Bank (2013), Central Bank of Bangladesh, https://www.bb.org.bd/econdata/exchangerate.php. BDT is the code for the Bangladeshi currency, the Taka.

Table 3. 2 Box-Cox Regression Estimates of the Out-of-Pocket Healthcare Expenditure Model ($\lambda^* \cong 0$)

Dependent variable: Healthcare expenditure			
Box-Cox regression	Estimator		
Different Box-Cox models	(I) Lambda model	(II) Left-hand-side–only model	(III) Right-hand-side–only model
Household's annual income	0.547* (0.060)	0.0000* (0.054)	1,912 (0.526)
Distance of residence from healthcare center/hospital	0.758 (0.119)	0.195 (0.159)	2,479 (0.297)
Age of household head	-2.454* (0.072)	-0.068 (0.260)	-1,316* (0.098)
Duration of illness episode	1.258*** (0.000)	0.019*** (0.003)	2,445** (0.062)
Years of schooling of household head	0.135 (0.803)	0.102 (0.609)	1,304 (0.616)
Family size	1.360 (0.335)	0.211 (0.596)	9,981 (0.154)
Marital status	0.563 (0.763)	-0.927 (0.624)	11,705 (0.163)
N	120	120	120

Note: p-values in parentheses. ***$p < 0.01$. **$p < 0.05$. *$p < 0.1$.

Table 3. 3 Box-Cox Regression Estimates of the Out-of-Pocket Healthcare Expenditure Model (lambda model) ($\lambda^{*} \cong 0$)

Dependent variable: Healthcare expenditure							
Box-Cox regression		Lambda model			Estimator		
Independent variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Household's annual income	0.718** (0.023)	0.714** (0.028)	0.714** (0.027)	0.606** (0.030)	0.605** (0.030)	0.531* (0.064)	0.468 (0.144)
Distance of residence from healthcare center/hospital		1.060** (0.046)	1.032** (0.049)	0.743 (0.125)	0.743 (0.125)	0.750 (0.123)	0.724 (0.137)
Age of household head			-1.381 (0.215)	-1.967* (0.053)	-1.955* (0.057)	-2.196** (0.038)	-2.601* (0.060)
Duration of illness episode				1.264*** (0.000)	1.263*** (0.000)	1.249*** (0.000)	1.265*** (0.000)
Years of schooling of household head					0.043 (0.936)	0.110 (0.837)	0.103 (0.849)
Family size						1.202 (0.358)	2.874 (0.312)
Marital status							0.933 (0.633)
Number of dependents in the household[11]							-1.146 (0.538)
N	120	120	120	120	120	120	120

Note: p-values in parentheses. ***p < 0.01. **p < 0.05. *p < 0.1.

[11] The number of dependents in the household is equal to the family size minus the number of earning members in the household.

Table 3. 4 Box-Cox Regression Estimates of the Out-of-Pocket Healthcare Expenditure Model (left-hand-side–only model) ($\lambda^* \cong 0$)

Dependent variable: Healthcare expenditure							
Box-Cox regression		Left-hand-side–only model				Estimator	
Independent variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Household's annual income	0.000** (0.014)	0.000** (0.019)	0.000** (0.021)	0.000** (0.016)	0.000** (0.017)	0.000** (0.040)	0.00* (0.089)
Distance of resident from healthcare center/hospital		0.274** (0.043)	0.278** (0.039)	0.187 (0.173)	0.193 (0.163)	0.194 (0.161)	0.196 (0.163)
Age of household head			-0.045 (0.327)	-0.077 (0.103)	-0.075 (0.118)	-0.085* (0.088)	-0.068 (0.266)
Duration of illness episode				0.019*** (0.002)	0.019*** (0.002)	0.019*** (0.002)	0.019*** (0.003)
Years of schooling of household head					0.088 (0.652)	0.113 (0.570)	0.102 (0.609)
Family size						0.279 (0.455)	0.192 (0.820)
Marital status							-0.939 (0.629)
Number of dependents in the household[12]							0.022 (0.980)
N	120	120	120	120	120	120	120

Note: p-values in parentheses. ***p < 0.01. **p < 0.05. *p < 0.1.

[12] The number of dependents in the household is equal to the family size minus the number of earning members in the household.

Table 3. 5 Box-Cox Regression Estimates of the Out-of-Pocket Healthcare Expenditure Model (right-hand-side–only model) ($\lambda^* \cong 0$)

Dependent variable: Healthcare expenditure							
Box-Cox regression		Right-hand-side–only model				Estimator	
Independent variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Household's annual income	116,275 (0.773)	17,347 (0.447)	17,044 (0.448)	2,054 (0.520)	2,521 (0.507)	1,398 (0.702)	1,433 (0.403)
Distance of resident from healthcare center/hospital		3,152 (0.235)	3,093 (0.244)	2,264 (0.343)	2,346 (0.334)	2,333 (0.334)	2,419 (0.284)
Age of household head			-5,649 (0.614)	-4,088 (0.506)	-5,113 (0.435)	-6,547 (0.320)	-10,046 (0.124)
Duration of illness episode				23,332* (0.078)	2,506* (0.071)	2,341* (0.087)	2,027** (0.063)
Years of schooling of household head					-2,266 (0.391)	-1,914 (0.469)	-1,067 (0.665)
Family size						6,501 (0.332)	1,831 (0.891)
Marital status							9,913 (0.124)
Number of dependents in the household[13]							5,511 (0.526)
N	120	120	120	120	120	120	120

Note: p-values in parentheses. ***p < 0.01. **p < 0.05. *p < 0.1.

[13] The number of dependents in the household is equal to the family size minus the number of earning members in the household.

APPENDIX

The distribution of different variables was prepared by the author based on the survey conducted by him. Here, Bangladeshi currency, the Taka (BDT),[14] is considered for the calculation of income, savings, and wealth.

Table A 3. 1 Household Head Age Group Distribution

Parameters	Frequency	Percentage
Age group (years)		
16–25	20	17
26–35	45	37
36–45	31	26
46–55	17	14
> 55	7	6

Source: Author's calculation from the survey conducted by him.

Table A 3. 2 Distribution of Years of Schooling of Household Head

Parameters	Frequency	Percentage
Years of schooling		
0	13	11
1–3	62	52
4–6	30	24.5
7–9	9	8
10–12	6	4.5

Source: Author's calculation from the survey conducted by him.

[14] Considering the exchange rate $1 = BDT 77.75 as of December 30, 2013, available on the website of Bangladesh Bank (2013), Central Bank of Bangladesh, https://www.bb.org.bd/econdata/exchangerate.php. BDT is the code for the Bangladeshi currency, the Taka.

Table A 3. 3 Distribution of Average Monthly Income of Households

Parameters	Frequency	Percentage
≤5,000	26	22
5,001–7,000	27	22.5
7,001–9,000	30	25
9,001–11,000	15	12.5
11,001–13,000	10	8
>13,000	12	10

Source: Author's calculation from the survey conducted by him.

Table A 3. 4 Distribution of Wealth Holding

Parameters	Frequency	Percentage
0	44	36.67
1–50,000	39	32.5
50,001–100,000	9	7.5
100,001–150,000	6	5
150,001–200,000	3	2.5
200,001–250,000	3	2.5
250,001–300,000	0	0
300,001–350,000	3	2.5
>350,000	13	10.83

Source: Author's calculation from the survey conducted by him.

Table A 3. 5 Distribution of Net Savings

Parameters	Frequency	Percentage
-50,000 to -20,000	8	6.67
-19,000 to -10,000	8	6.67
-9,999 to -1	18	15
0	47	39.2
1 to 10,000	29	24.2
10,001 to 20,000	4	3.33
>20,000	6	5

Source: Author’s calculation from the survey conducted by him.

Table A 3. 6 Distribution of Marital Status

Parameters	Frequency	Percentage
Married	94	78
Unmarried	26	22

Source: Author’s calculation from the survey conducted by him.

Table A 3. 7 Distribution of Number of Sick Days of RP Households

Parameters	Frequency	Percentage
0	9	7.5
1–30	70	58.33
31–60	20	16.67
61–90	10	8.33
>90	11	9.17

Source: Author’s calculation from the survey conducted by him.

Table A 3. 8 Distribution of Number of Family Members of RP Households Taking any Drug

Parameters	Frequency	Percentage
Not taking	19	15.83
Taking	101	84.17

Source: Author’s calculation from the survey conducted by him.

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The 2019 Conference of Florida Graduate Schools (CFGS), Florida Statewide Graduate Student Research Symposium, Florida International University, Miami, Florida, April 17-18,2019.

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Eastern Economic Association’s 44th Annual Conference, Boston Sheraton, Boston MA, March 1 - 4, 2018.

Graduate Student Appreciation Week (GSAW), Graduate and Professional Student Committee (GPSC), Graduate Advisory Board, and the University Graduate School, Florida International University (FIU), March 19 - 20, 2018.

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